Assembling Technique Based on the Statistical Feed-Forward Control Model for Low Precision Manufacturing Processes

Von der Fakultät für Maschinenbau
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ERKLÄRUNG

Hiermit erkläre ich, dass ich die vorliegende Arbeit - mit Ausnahme der in ihr ausdrücklich genannten Hilfen - selbständig verfasst habe.

Carlos Hernández

ZUSAMMENFASSUNG

Die Beiträge dieser Arbeit zum Ingenieurwissen sind das hier vorgestellte *Statistical Feed-Forward Control Model* (SFFCM) als Kern einer innovativen Montage-Technik und die *Statistical Dynamic Specifications Method* (SDSM), um dynamische Spezifikationen und Toleranzen zu verwalten.

Die Montage von Komponenten aus Fertigungsprozessen gekennzeichnet durch hohe Maßabweichungen wurde traditionell aus zwei unterscheidbaren Perspektiven betrachtet: die selektive und die adaptive Montage. Moderne Techniken aber verwenden in der Regel eine Kombination dieser Ansätze. Der größte Nachteil der selektiven Montagetechniken ist die Notwendigkeit zum Inspizieren von 100% der Elemente, so dass sie klassifiziert und anschließend zusammengebaut werden können. Die adaptiven Montagetechniken berücksichtigen in der Regel nicht die Evolution der Variation über die Zeit sondern nur die zuletzt untersuchte Probe, um die vorzunehmenden Anpassungen abzuschätzen. Keiner dieser Ansätze betrachtet die Variation als eine Überlagerung verschiedener Variationsarten.

Diese Arbeit nimmt die Herausforderung an, eine neuen Montage-Technik zu entwickeln, um die Herstellung von Baugruppen geringer Variation durch Paarung von Komponenten hoher Variation zu erreichen. Die wichtigsten Ergebnisse des vorgeschlagenen Modells sind die Reduzierung der resultierenden Variation, die Reduzierung der Ausschussrate und die Verbesserung der Prozessfähigkeits-Indizes.

Mit Hilfe der speziell entwickelten *Dynamic Assembling Simulation Software* (DASS) wurde eine große Reihe von Experimenten entwickelt, um die Produktion von vielen 1.000 Tsd. Baugruppen aus zwei Komponenten hoher Variation zu simulieren, so dass die einzelnen und kombinierten Einflüsse verschiedener die Produktion betreffender Faktoren ausgewertet werden können.

Die Simulationsergebnisse zeigten, im Vergleich zur vollständig randomisierten Montage, eine durchschnittliche Reduktion des verschobenen Erwartungswerts um 89% (von einem Mittelwert 29.55 mm zu einem verbesserten Mittelwert 29.95 mm bei einem nominellen Zielwert von 30.00 mm), eine durchschnittliche Reduktion der Standardabweichung um 14% (von 0.29 auf 0.25), eine durchschnittliche Verbesserung des Prozessfähigkeitsindex c_p des Montageprozesses um 16% (von 1.15 auf 1.34), eine durchschnittliche Verbesserung des Prozessfähigkeitsindex c_{pk} des Montageprozesses um 101% (von 0.63 auf 1.27) und eine

durchschnittliche Reduktion der Elemente außerhalb der Toleranz um 100% (von 28.6 pro tausend Paarungen auf Null).

Im Ergebnis trägt die vorgeschlagene SFFCM-basierte Montagetechnik, eine Kombination des adaptiven und selektiven Ansatzes mit Schwerpunkt auf der Inspektionsoptimierung, wirksam dazu bei, die Hauptziele dieser Arbeit zu erreichen: reduzieren der Prozessvariation, reduzieren der Ausschussrate und verbessern der Prozessfähigkeitsindizes. Zusammengefasst ist es möglich, mit Komponenten hoher Streuung zu Baugruppen mit geringer Maßabweichung zu gelangen. Aus einer anderen Perspektive betrachtet wurde ein fähiger Prozess (c_p >1.33) durch die Kombination zweier nicht fähiger Teilprozesse erreicht.

Promotionskommission:

Herrn Prof. Dr.-Ing. Uwe Dombrowski (Vorsitzender)

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Assembling Technique Based on the Statistical Feed-Forward Control Model
for Low Precision Manufacturing Processes

by

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ABSTRACT

The contributions of this thesis to engineering knowledge are the Statistical Feed-Forward Control Model (SFFCM) as the core of the novel assembling technique proposed here and the Statistical Dynamic Specifications Method (SDSM) to manage dynamically targets and tolerances.

The assembly of components coming from manufacturing processes characterized by high dimensional variation has been traditionally approached from two distinguishable perspectives: selective and adaptive assembling. Modern techniques, however, usually adopt a combination of these approaches. The mayor downside of the selective assembling techniques is the need for inspecting 100% of the component items so that they can be classified to be assembled afterwards. The adaptive assembling techniques usually do not consider the evolution of the variation over time and only take into account the last inspected sample to estimate the adjustments that have to be made. None of these approaches consider the nature of the variation as a superposition of different variation forms.

This thesis embraces the challenge of developing a new assembling technique to deal with the problem of producing low variation assemblies by means of mating high variation components. The main objectives of the proposed model are the reduction of the resulting variation, the reduction of the scrap levels and the improvement of the process capability indices.

With the help of the specially developed Dynamic Assembling Simulation Software (DASS), a large set of experiments was designed to simulate the production of lots of one

thousand assemblies made of two high variation components so that the individual and combined influence of the factors involved in the production can be evaluated.

For an assembly process with a nominal target value of 30 mm, simulation results revealed, in comparison to a fully randomized assembling, an average reduction by 89% of the mean shift from a mean value equal to 29.55 mm to an improved mean equal to 29.95 mm, an average reduction by 14% of the standard deviation from 0.29 to 0.25, an average improvement of the actual capability index of the assembling process by 16% from 1.15 to 1.34, an average improvement of the potential capability index of the assembling process by 101% from 0.63 to 1.27, and an average reduction of the items out of tolerance by 100% from 28.6 per thousand opportunities to zero.

In conclusion, the proposed SFFCM-based assembling technique, a combination of the adaptive and the selective approach with emphasis in the inspection optimization, effectively helped achieve the mayor objectives of this thesis: reduce the process variation, reduce the scrap level and improve the process capability indices. In few words, it is possible to end up with low variation assemblies made of high variation components. Seen from a different perspective, a capable process (c_p>1.33) was obtained by means of combining two non-capable subprocesses.

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Braunschweig, March 2013 Carlos Hernández

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ACRONYMS

ASA	Adaptive and Selective Assembling
CDNA	Cumulative de-Noised Average
CTQ	Critical To Quality
DASS	Dynamic Assembling Simulation Software
DMAIC	Definition, Measurement, Analysis, Improvement, and Control
ISO	International Organization for Standardization
LTL	Lower Tolerance Limit
MSE	Mean Square Error
MTA	Make To Assemble
MTO	Make To Order
MTS	Make To Stock
OSA	Ordered Selective Assembling
PCI	Process Capability Index
PDF	Probability Density Function
PID	Proportional Integral Derivative
QC	Quality Control
QE	Quality Engineering
QMS	Quality Management System
SAPS	Selective and Adaptive Production Systems
SDSM	Statistical Dynamic Specifications Methods
SFFCM	Statistical Feed-Forward Control Model
SPC	Statistical Process Control
SQC	Statistical Quality Control
TCS	Total Customer Satisfaction
TPM	Total Productive Maintenance
TQC	Total Quality Control
TQM	Total Quality Management
UTL	Upper Tolerance Limit
2D	Two-Dimensional
3D	Three-Dimensional

NOMENCLATURE

Statistic	Estimator	Description
c_p	$\hat{c}_p$	Potential capability index.
$c_{p,assy}$	$\hat{c}_{p,assy}$	Potential capability index of the assembly process.
$c_{p,assy,adj}$	$\hat{c}_{p,assy,adj}$	Potential capability index of the assembly process after SFFCM.
$c_{p,i}$	$\hat{c}_{p,i}$	Potential capability index of the process of Component *i*.
$c_{p,i,sub(j)}$	$\hat{c}_{p,i,sub(j)}$	Potential capability index of the subset *j* of the process of Component *i*.
$c_{p,i,adj,sub(j)}$	$\hat{c}_{p,i,adj,sub(j)}$	Potential capability index of the subset *j* of the process of Component *i* after SFFCM.
$c_{pk,assy}$	$\hat{c}_{pk,assy}$	Actual capability index of the assembly process.
$c_{pk,assy,adj}$	$\hat{c}_{pk,assy,adj}$	Actual capability index of the assembly process after SFFCM.
c_{pk}	$\hat{c}_{pk}$	Actual capability index.
$c_{pk,i}$	$\hat{c}_{pk,i}$	Actual capability index of the process of Component *i*.
$c_{pk,i,sub(j)}$	$\hat{c}_{pk,i,sub(j)}$	Actual capability index of the subset *j* of the process of Component *i*.
$c_{pk,i,adj,sub(j)}$	$\hat{c}_{pk,i,adj,sub(j)}$	Actual capability index of the subset *j* of the process of Component *i* after SFFCM.
L_{assy}	-	Nominal target of the assembly.
L_i	-	Nominal target of Component *i*.
$L_{i,adj,sub(j)}$	$\hat{L}_{i,adj,sub(j)}$	Adjusted target of the subset *j* of Component *i*.
μ_{assy}	$\bar{x}_{assy}$	Mean and sample mean of the assembly.
$\mu_{assy,sub(j)}$	$\bar{x}_{assy,sub(j)}$	Mean and sample mean of the subset *j* of the assembly.
μ_i	$\bar{x}_i$	Mean and sample mean of Component *i*.
$\mu_{i,sub(j)}$	$\bar{x}_{i,sub(j)}$	Mean and sample mean of the subset *j* of Component *i*.
σ_{assy}	s_{assy}	Std.Dev. and sample Std.Dev. of the assembly.
σ_i	s_i	Std.Dev. and sample Std.Dev. of Component *i*.

Statistic	Estimator	Description
$\sigma_{i,sub(j)}$	$s_{i,sub(j)}$	Std.Dev. and sample Std.Dev. of the subset *j* of Component *i*.
t_{assy}	-	Nominal tolerance of the assembly.
t_i	-	Nominal tolerance of Component *i*.
$t_{i,adj,sub(j)}$	$\hat{t}_{i,adj,sub(j)}$	Adjusted tolerance of the subset *j* of Component *i*.
$t_{i,adj,sub(j),unc}$	$\hat{t}_{i,adj,sub(j),unc}$	Adjusted tolerance of the subset *j* of Component *i* considering the measurement uncertainty.
-	$\overline{x}_{cdna}$	Cumulative de-noised average.
-	$\overline{x}_{i,cdna}$	Cumulative de-noised average of Component *i*
-	$\overline{x}_{i,cdna,sub(j)}$	Cumulative de-noised average of the subset *j* of Component *i*

1. INTRODUCTION

1.1. Overview

Serial production relies on the availability of interchangeable items whose characteristics are so nearly identical that any of them can be assembled in a given device without any kind of modification. However, manufacturing processes are constantly under the influence of different sources of variation which, in practice, make it almost impossible to fabricate two identical items of the same component. Commonly, in the literature these sources of variation are classified in six groups: people, methods, machines, materials, environment and measurements (Figure 1-1).

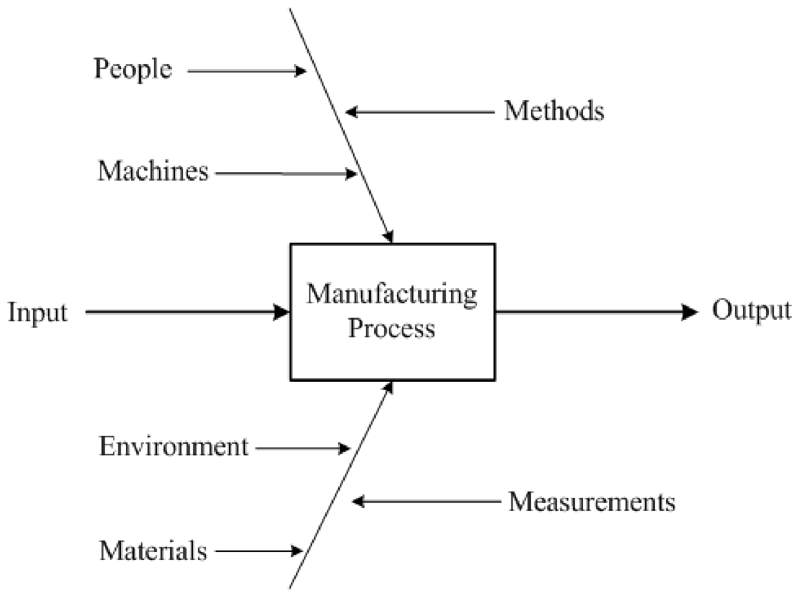


Figure 1-1. Sources of variation.

Even though dimensional variation affects directly the ability of a process to produce units that meet the desired specifications, in reality, component items do not need to be strictly identical as long as they are within a certain level of tolerance previously defined. Thus, the tolerance can be defined as the admissible variation for a given geometric dimension. A product, either a single component or a whole assembly, will be only considered “good” if it is manufactured and measured within its tolerance range. Otherwise, it will be considered “defective”.

Although often regarded as the cornerstone of serial production, under certain circumstances, the general applicability of the principle of interchangeability can be discussed. A good example can be found in the assembling of component items coming from processes that are known for producing units with high dimensional variation. There, the dimensional variation of the resulting assemblies depends so much on the specific selection of the mated items that a randomized assembling might produce a large number of defective assemblies.

Usually, the fabrication of modern devices and electronic gadgets requires sophisticated equipment and high-qualified labor. Therefore, when they break down it might be more reasonable to replace them by a good one rather than attempting a complicated and probably costly repair. This fact provides another reason to question the rigidness of the interchangeability principle and to explore alternative assembling techniques that are more suitable for those manufacturing processes whose final products are not meant to be repairable.

1.2. Initial Hypothesis

The assembly of high variation component items that are taken randomly from independent normally distributed lots will give rise to assemblies having even higher dimensional variation. The underlying mathematical fundament and statistical proof of this fact are explained with great detail in Appendix B.

Through the years, several assembling techniques have been proposed to approach those situations in which all the efforts to neutralize the influence of the sources of variation have failed. Three groups can be mentioned: selective techniques, adaptive techniques and more recently, combined techniques.

The initial hypothesis of this thesis is that the dimensional variation of the resulting assemblies can be reduced by means of managing dynamically the target and tolerance of the assembled components. In other words, the output parameters μ_{assy} and σ_{assy} can be controlled from within the system by means of adjusting some of the inner process parameters (Figure 1-2).

In the same way that the variation sources affect the production of individual components, the assembling process itself is subject of variation. In this work, however, the analysis is not centred on those factors or “uncontrollable inputs” but on what it can be done within the process by means of managing the “controllable inputs”.

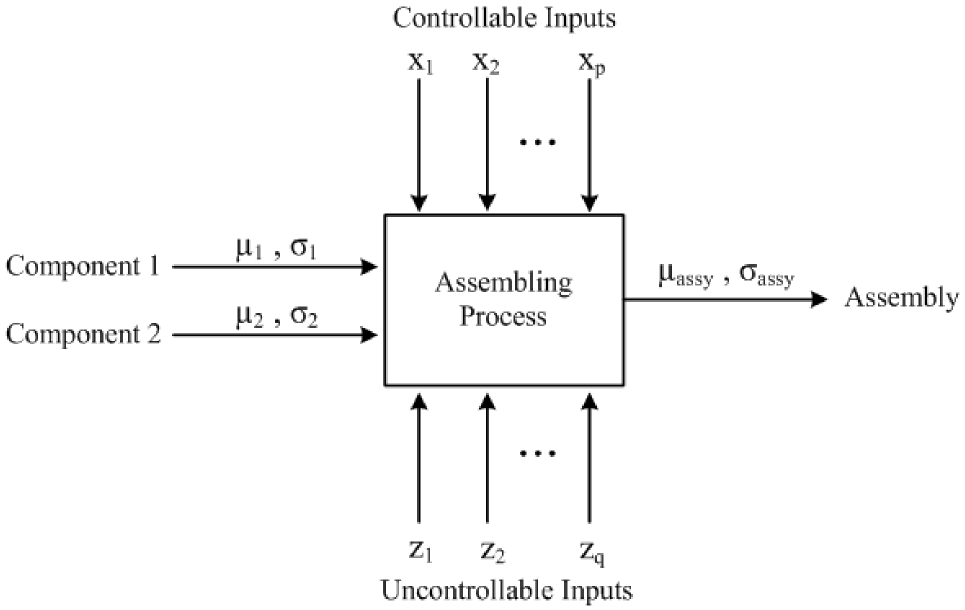


Figure 1-2. Inputs of an assembling process.

1.3. Research Objectives

The main objective of this work is to develop an assembling technique to deal with the problem of assembling high variation components coming from low precision processes. Specifically, the proposed technique has to be effective in:

1. reducing the dimensional variation of the resulting assemblies,
2. minimizing the scrap level, and
3. improving the process capability indices.

Several intermediate objectives need to be completed in every stage of the research:

1. Identify possible gaps and improvement opportunities in the existing assembling techniques,
2. Study different probability distributions, their statistical properties and possible applications,
3. Develop a method to adjust the inner process parameters in a way that the process' output can be controlled from within the process,
4. Develop a technique to select those component items whose dimensions complements each other to produce assemblies within the specifications.
5. Develop a piece of software to simulate experiments and to test the proposed techniques.

6. Carry out enough experiment simulations to quantify the influence of those factors that might play a role in the proposed model.

1.4. Approach and Methodology

In this work the assembling process is considered an open-box that comprises a collection of subprocesses which can be matter of individual observation. Eventually, that observation could make possible the early detection of fluctuations in the variables of interest.

The general idea proposed in this thesis is the introduction of a measurement step in some middle point of the assembling line to obtain information about the fluctuation of the variables of interest. A feed-forward controller retrieves data and determines the necessary adjustments that should be applied on the parameters of a subsequent subprocess (Figure 1-3).

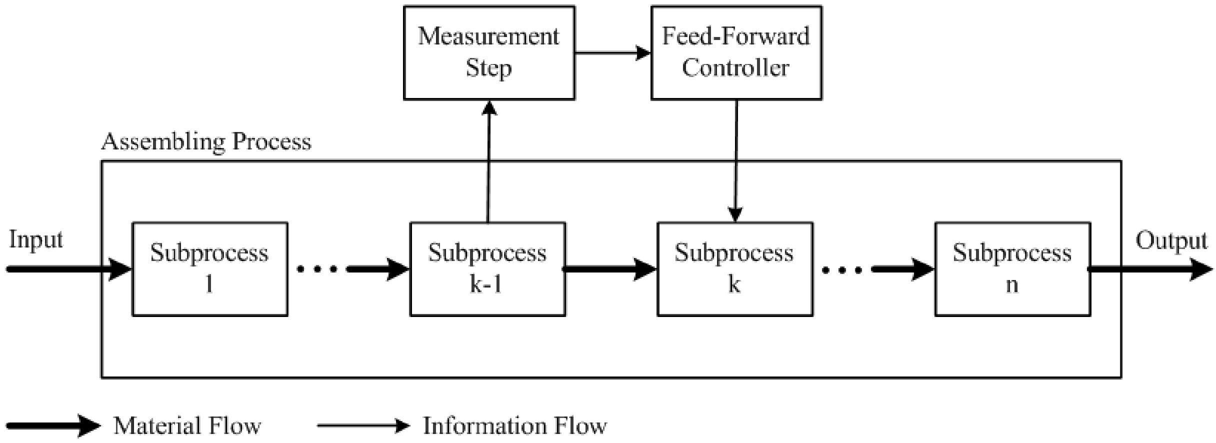


Figure 1-3. Subprocesses within the assembling process.

To assist calculating the proper specification adjustments, target and tolerance, a novel Statistical Dynamic Specification Method (SDSM) is proposed. Whereas the scrap level is expected to be reduced by means of allocating extended tolerances; the adjusted targets are expected to force the resulting assemblies meet their nominal target.

To deal with the dynamic nature of the variation and its evolution over time a novel Statistical Feed-Forward Control Model (SFFCM) is proposed. With it, the control over the assembling subprocesses is exerted by means of applying repeatedly SDSM to small groups of component items produced consecutively in a short-time interval.

To simulate the implementation of SDSM and SFFCM in a production environment, the Dynamic Assembling Simulation Software (DASS) was developed. This software was designed to be a fully customizable tool that is able to simulate the production of lots of multi-component assemblies in a wide range of different scenarios and to replicate automatically the experiments as many times as desired.

The applicability of the proposed SDSM and SFFCM was evaluated by means of simulating massively the production of lots of multi-component assemblies in different scenarios. Large sets of experiments aimed to quantify the individual and combined influence of different factors on the process output were designed, simulated and replicated several hundreds of times.

In concordance with the initial hypothesis and taking as reference the results of a fully randomized assembling, the effectiveness of the proposed technique was measured in terms of the reduction of the mean shift and the standard deviation of the resulting assemblies, and the reduction of the scrap level and the improvement of the process capability indices.

1.5. Thesis Structure and Research Advancements

The thesis is organized in six chapters. A short description of the content and the research advancements of each chapter are given in this section.

Chapter 1: The motivation to carry out the research is given. The initial hypothesis, the objectives and methodology to realize them are presented too. At the end, the thesis' structure is given as well.

Research Advancements

- Presents the motivation and describes the problem to be solved.
- States the initial hypothesis and the methodology to carry out the research.

Chapter 2: Existing selective, adaptive and combined assembling techniques are presented in this chapter along with a critical review of the current practices.

Research Advancements

- Provides some basic definitions of concepts used in manufacturing.
- Presents several selective, adaptive and combined assembling techniques.
- Gives a critical review of the existing assembling techniques, reveals their downsides and explains some improvement opportunities.
- Defines the characteristics of an innovative assembling technique that combines selective and adaptive features.
- Gives a brief overview of several quality management techniques.

Chapter 3: Theoretical background about tolerance stacking methods, normal distributions, statistical models and process control is given. The proposed SDSM and SFFCM are introduced in this chapter as well.

Research Advancements

- Presents several tolerance stacking methods.
- Summarises some of the properties of the normal distributions and several important theorems in statistics.
- Presents some notions about statistical process control.
- Introduces the Statistical Dynamic Specifications Method (SDSM).
- Introduces the Statistical Feed-Forward Control Model (SFFCM).

Chapter 4: Modules and functionalities of the Dynamic Assembling Simulation Software (DASS) are explained. From the generation of the component lots by mean of Monte Carlo simulations to the 3D plotting of the resulting assemblies and passing through complex mathematical algorithms implemented in the prediction module, the mayor features of DASS are explained in detail in this chapter.

Research Advancements

- Introduces DASS, its principal modules and features.
- Explains in detail some of the most important algorithms of DASS.
- Explains the application of SFFCM to parallel manufacturing schemes.

- Explains the implementation of an external feedback loop to complement the proposed feed-forward loop.
- Introduces the strategy adopted to maintain DASS performance during heavy simulation regimes.

Chapter 5: Simulation results are presented with great detail in this chapter. Results are classified and grouped according to the type of experiment they belong with. Abundant tables, plots, explanations and discussions are provided as well.

Research Advancements

- Presents simulation results corresponding to every group of experiments.
- Explains and discusses the results with plenty of plots and tables.
- Reveals the parameters' values that give rise to the best results.

Chapter 6: A summary of the work and final conclusions are presented in this chapter. Possible alternatives to extend this line of research are also given and discussed.

Research Advancements

- Provides the final conclusions of this thesis.
- Proposes several alternatives to continue the research.

1.6. Chapter Summary

In the first sections of this chapter, a general overview of the serial production and the importance of the interchangeability principle are provided to explain the motivation for conducting this research and to formulate the problem to be solved. The initial hypothesis, research objectives and the methodology are presented as well. In the final section, the thesis' structure and the contents and mayor research advancements of each chapter are given.

2. MANUFACTURING PROCESSES AND ASSEMBLING TECHNIQUES

Chapter Highlights

- Provide definitions used in manufacturing.
- Present existing selective, adaptive and combined assembling techniques for low precision processes.
- Give a critical review of current practices.
- Establish the requirements for a new assembling technique.
- Describe modern quality management techniques.

2.1. Introduction

Manufacturing usually involves the assembly of several component items to produce a final product. These items are fabricated in such a way that no additional modification is needed to assemble or replace them, as it is suggested in the principle of interchangeability. However, since all manufacturing processes are influenced by diverse sources of variation, in reality, it is not simple to produce two identical units of the same part.

Through the years, along with different process control models aimed to diminish or even to neutralize the influence of the variation sources a good number of assembling techniques for mating high variation items have been developed. In this chapter some of the existing selective, adaptive and combined techniques are described and analyzed.

2.1.1. Overview

This chapter focuses on the description and analysis of the available assembling techniques for low precision processes.

Chapter Goals

- Determine advantages and downsides of existing selective, adaptive and combined assembling techniques for high variation components.
- Identify possible gaps and improvement opportunities in the current practices.
- Define the requirements for an alternative assembling technique.
- Provide basic notions about modern quality management techniques.

2.1.2. Background

In technical literature production and manufacturing are often considered synonyms and even interchangeable terms. However, it is possible to establish a thin difference between them. Indeed, manufacturing has a narrower meaning. Whereas production can be seen as a process in which inputs are transformed into outputs; manufacturing can be understood as the process of converting raw materials into final products. According to that, all kinds of manufacturing might be considered production but not all type of production would be manufacturing (Figure 2-1).

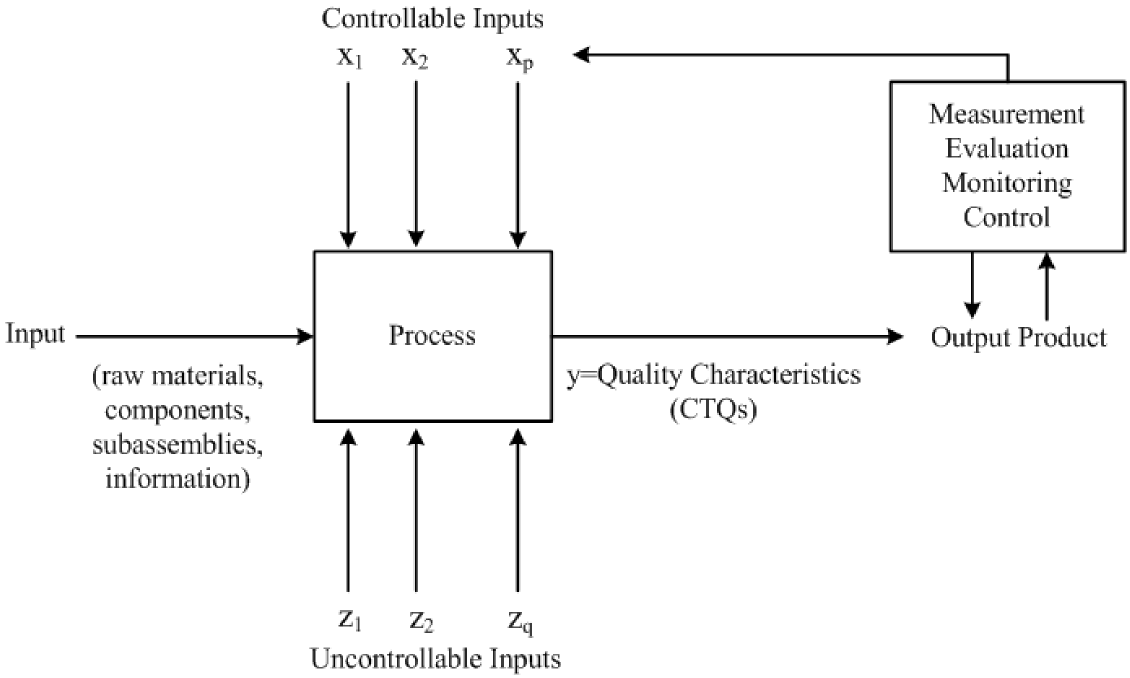


Figure 2-1. Conceptual process [Mon09 ch.1].

From the point of view of the logistic, three different types of manufacturing can be distinguished: make-to-stock (MTS), make-to-order (MTO) and make-to-assemble (MTA) [Ghi04 ch.1 pp.5-6].

1. In MTO systems, finished products are manufactured only when they are required. Hence, in principle, no inventories are needed. MTO systems are suitable whenever lead times are short, products are costly, and demand is low and highly variable. Manufacturers might alleviate inventory problems with MTO, but clients usually have to wait longer.
2. In MTS systems, production and distribution decisions are based on forecasts. Thus, production anticipates effective demand, and enough inventory levels are kept in store. MTS makes sense when demand can be predicted with reasonable accuracy. Manufacturers might lose money if the forecast is wrong and if they produce too much or too little.
3. In MTA systems, components and semi-finished products are manufactured in a push-based manner while the final assembly stage is pull-based. Hence, the work-in-process inventory at the end of the first stage is used to assemble the finished product as demand arises. These parts are then assembled as soon as orders are received. MTA is a combination of MTO and MTS. Companies stock basic parts based on demand predictions, but do not assemble them until clients submit orders [Ghi04 ch.1 pp.5-6].

2.1.2.1. Principle of Interchangeability

According to Buckingham [Buc21 ch.1 p.1], interchangeable manufacturing consists of machining the component items within such limits that they may be assembled without fitting or further machining. Component items may also be replaced or transferred from one assembly to another without detriment to the functioning and without machining.

In practice, interchangeable items are identical only up to certain point. They are made to specifications that guarantee that their characteristics and dimensions are so close to one another that they fit into any assembly of the same type without any modification. Thus, the assembly of new devices and the repair of old ones is significantly simplified.

2.2. Production Line

Production lines can be seen as the organized interaction of operators, machines and tools over a continuous flow of component items that are added sequentially to create final products.

One of the most famous production models is that one implemented for Model T by Ford Motor Company. According to Henry Ford the principles of assembly can be stated as follows [For22 ch.5 p.41]:

1. Place the tools and the men in the sequence of the operation so that each component part shall travel the least possible distance while in the process of finishing.
2. Use work slides or some other form of carrier so that when a workman completes his operation, he drops the part always in the same place, which place must always be the most convenient place to his hand, and if possible have gravity carry the part to the next workman for his operation.
3. Use sliding assembling lines by which the parts to be assembled are delivered at convenient distances.

2.2.1. Propagation of Variation

Hu et al. [Hu97] proposed the Stream of Variation Theory to explain the propagation of variation in manufacturing systems that consist of processes and machines in a multi-level hierarchy. According to this theory, the resulting dimensional variation in the final product is accumulated as the product moves along the production line.

Agrawal et al. [Agr96] proposed the inclusion of the measurement error in a new mathematical theory to quantify the variation transmission in multi-stages manufacturing processes. They started for the already known idea of measuring individual parts as the process progresses; using a simple regressive model to estimate the amount of variation that is added at each stage, and the amount that is transmitted upstream. This idea makes possible to associate components of variation in the final product's characteristics with different stages providing guidance for variation reduction activities.

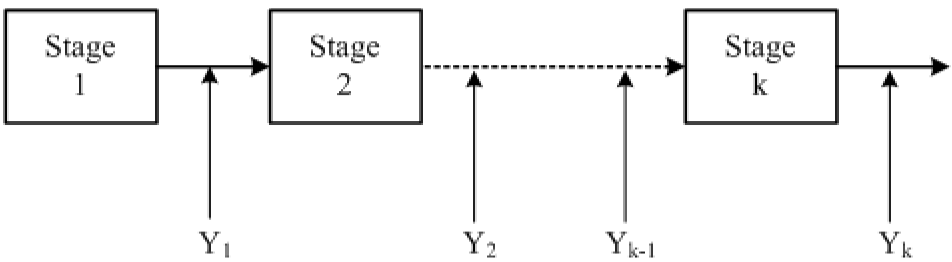


Figure 2-2. Propagation of variation [Agr96 p.2].

In this model, originally proposed by Lawless et al [Law99], Y_k is the cumulated final quality characteristic (CTQ) of a k-stage-process; whereas Y_i is the single characteristic that can be measured right after the stage i. The normally assumed distribution of Y_i, given the history of the item up to stage *(i-1)*, depends only on Y_{i-1}. This shown in the following equations:

$$Y_i \sim N\left(\mu_i, \sigma_i^2\right) \tag{2-1}$$

$$Cov(Y_{i-1} - Y_i) = \rho_{i-1,i}\sigma_{i-1}\sigma_i \qquad i \geq 2 \tag{2-2}$$

where μ is the mean, σ is the standard deviation and ρ is the correlation coefficient.

2.3. Assembling Techniques

The assembling can be seen as the action of adding up different component items to create a finished product. A number of approaches have been proposed for diverse purposes. This section is limited to those assembling techniques applicable to low precision processes that give rise to high variation component items.

2.3.1. Randomized Assembling

In a randomized assembling scheme all the items of a given component have the same probability of being drawn to be assembled. As long as the dimension of the items falls within the admissible tolerance range, there will be no impediment to implement this technique. However, when the defined range of dimensional variation cannot be held, a randomized assembly might not be an appropriate choice.

2.3.2. Selective Assembling Techniques

Buckingham [Buc21 ch.2 p.18] described selective assembling as a method of manufacturing in which component items are sorted and mated according to size and assembled or interchanged with little or no modification.

Mansoor [Man61] recalled the British Standard 2517:1954 to provide a formal definition as follows: ”Selective Assembly is a procedure in which parts of anyone type are classified into several groups according to size. The parts which are intended to be mated with these are also classified according to size in the same number of groups. Corresponding groups are then expected to assemble and to function properly".

The randomness of this technique has been matter of discussion in the past, some authors argued that selective assembly merely grades the parts into several ranges; within each range, however there is still random interchangeability.

This technique permits the economical manufacture of both components making the fit, these are then graded into categories or bins by 100% inspection, and then items from matched categories are selected for assembly on the basis of interchangeability [Man61] (Figure 2.3).

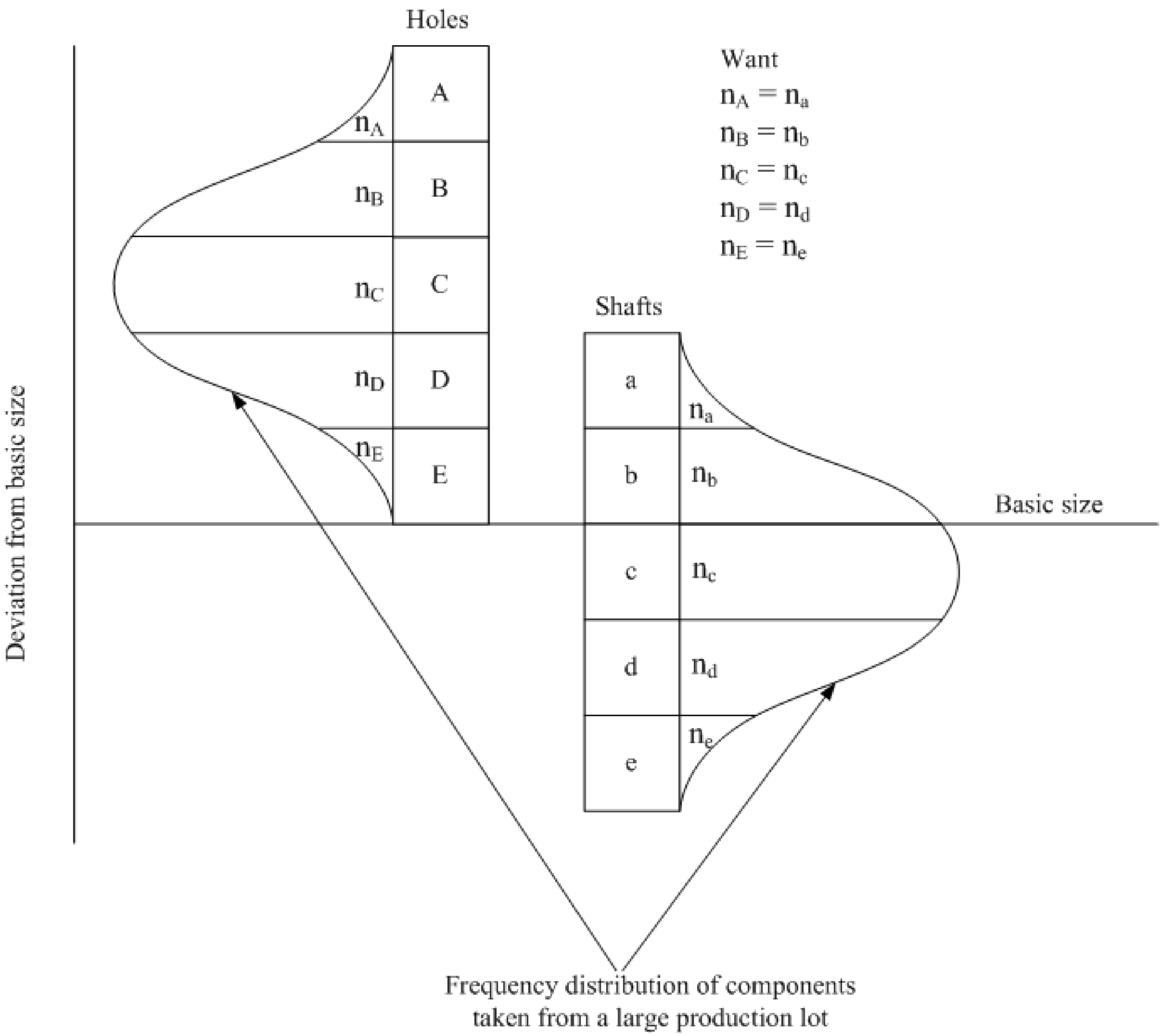


Figure 2-3. Corresponding categories in selective assembling [Man61 p.14].

Manufacturing processes often generate dimensions that are normally distributed, being this assumption commonly taken for granted in the literature. However, it might not be the case. In fact, manufacturing processes can generate dimensions in an infinite number of irregular distributions. Kern [Ker03 ch.4 p.180] analyzes the application of selective assembling on populations that are not normally distributed.

Different selective assembling techniques conceived to minimize either the scrap or the variation have been proposed through the years. Some of them are described in the next sections which are based on the modern classification proposed by Kern [Ker03 ch.4 p.143].

2.3.2.1. Equal Width Binning to Minimize Variation

In this technique, the bin width is the same for both components' distributions, which are assumed to be normal. The bin width is determined by the tighter distribution which is truncated at *-3σ* and at *+3σ*. The range, equal to six standard deviations, is then divided by N, the desired number of bins, to produce the bin width.

$$bin_{wide} = bin_{tight} = \frac{6\sigma_{tight}}{N} \tag{2-3}$$

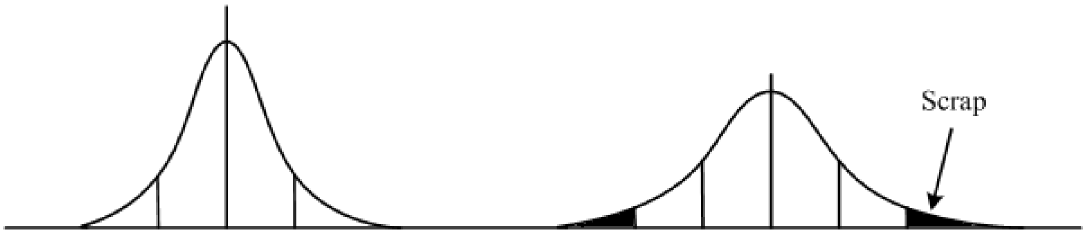


Figure 2-4. Equal width binning to minimize variation [Ker03 ch.4 p.145].

Advantages

1. The resulting assembly variance can be significantly reduced.
2. Since the bin width calculations are simple, the bin widths can be quickly adjusted if needed.

Disadvantages

1. Considerable amount of scrap that can result from truncating the wider distribution, particularly, when the variances of the two distributions are very different.

2.3.2.2. Equal Width Binning to Minimize Scrap

Different from the previous case, in this case the bin width is unique to each distribution. However, the number of bins N in both cases is equal. To compute the bin widths the distributions have to be truncated at plus and minus three standard deviations.

$$bin_{tight} = \frac{6\sigma_{tight}}{N} \tag{2-4}$$

$$bin_{wide} = \frac{6\sigma_{wide}}{N} \quad (2\text{-}5)$$

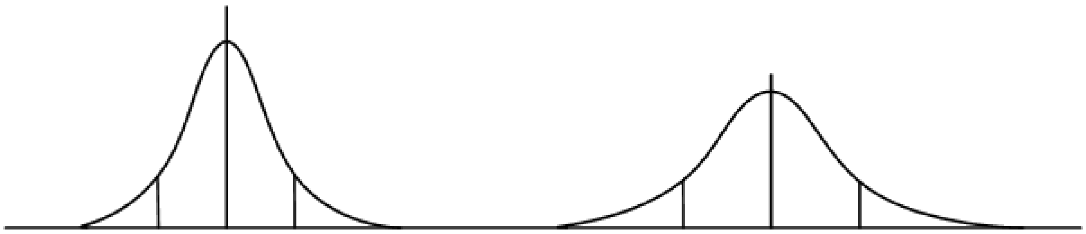


Figure 2-5. Equal width binning to minimize scrap [Ker03 ch.4 p.146].

Advantages

1. Since the wider distribution is not truncated to match the tighter distribution, there is not additional scrap other than the corresponding to the truncated tails.
2. The bin widths for each population are independent and can be easily recalculated if the variance of one distribution changes.

Disadvantages

1. The range of assembly dimensions depends on which set of corresponding bins is used.
2. Even though this technique will hardly reduce the variation of the assembly dimension, the results are still significantly better in comparison to a fully randomized assembling.

2.3.2.3. Equal Area Binning to Minimize Variation

In this technique, the width of each bin is defined in such a way that a certain percentage of area under the probability density function (PDF) is contained within each bin. The limits of the bins are determined by the tighter distribution but the bin widths are the same for both distributions.

Just like in previous techniques, the tighter distribution is truncated at -3σ and at $+3\sigma$ and the area under the remaining truncated curve is then divided by the desired number of bins N. The wider distribution is truncated and then divided into bins according to the widths specified by dividing the tighter distribution. Due to the shape of the probability density function of normal distributions, the bins at the center are expected to be narrower than the ones at the tails.

$$bin_{tight,i} = bin_{wide,i} = x_i - x_{i-1} \tag{2-6}$$

$$\frac{1}{N} = \int_{x_{i-1}}^{x_i} \left(pdf_{tight} \right) dx \tag{2-7}$$

In the case of normal distributions equation (2-7) can be reformulated as follows:

$$\frac{1}{N} = \int_{x_{i-1}}^{x_i} \left(\frac{1}{\sigma_{tight}\sqrt{2\pi}} \exp\left\{ -\frac{1}{2} \left(\frac{x-\mu_{tight}}{\sigma_{tight}} \right)^2 \right\} \right) dx \tag{2-8}$$

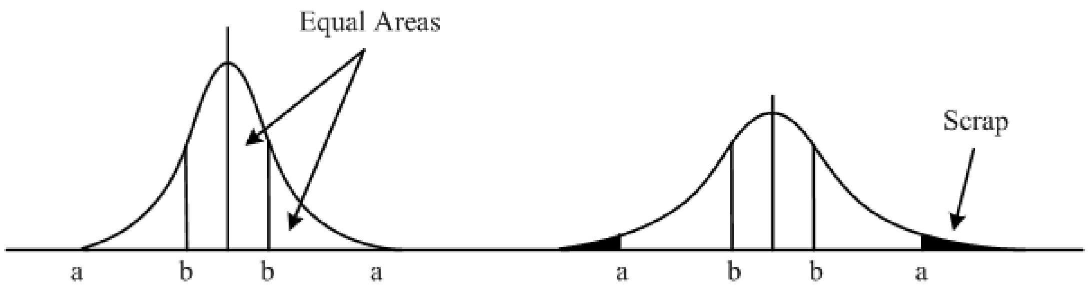


Figure 2-6. Equal area binning to minimize variation [Ker03 ch.4 p.148].

Advantages

1. The resulting assembly variance can be significantly reduced.

Disadvantages

1. The truncation of the wider distribution might generate a considerable amount of scrap, In particular, when the variances of the two distributions are very different.
2. The possible range of assembly dimensions may be significant. In particular, when items from two corresponding larger bins near the tails are combined.

2.3.2.4. Equal Area Binning to Minimize Scrap

In this technique, the width of each bin is set in such a way that a certain percentage of area under the probability density function is contained within the bin. The two distributions are binned independently. As usual, the distributions are truncated at plus or minus three standard deviations. The areas under the remaining truncated curves are then divided by the desired number N of bins.

$$bin_{tight,i} = x_i - x_{i-1} \tag{2-9}$$

$$bin_{wide,i} = y_i - y_{i-1} \tag{2-10}$$

$$\frac{1}{N} = \int_{x_{i-1}}^{x_i} \left(\frac{1}{\sigma_{tight}\sqrt{2\pi}} \exp\left\{ -\frac{1}{2}\left(\frac{x-\mu_{tight}}{\sigma_{tight}} \right)^2 \right\} \right) dx \tag{2-11}$$

$$\frac{1}{N} = \int_{y_{i-1}}^{y_i} \left(\frac{1}{\sigma_{wide}\sqrt{2\pi}} \exp\left\{ -\frac{1}{2}\left(\frac{x-\mu_{wide}}{\sigma_{wide}} \right)^2 \right\} \right) dx \tag{2-12}$$

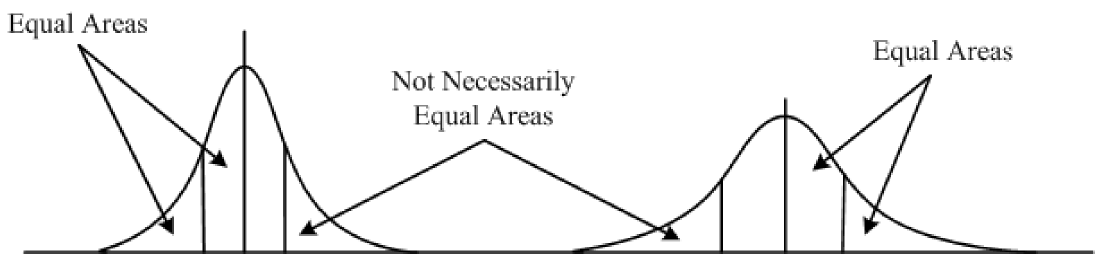


Figure 2-7. Equal Area Binning to Minimize Scrap [Ker03 ch.4 p.151].

Advantages

1. The wider distribution is not truncated to fit the tighter one. Thus, no additional scrap other than the corresponding to the truncated tails is generated.

Disadvantages

1. Since the bins near the tails are much wider than those near the middle, especially in the wider distribution, the possible range of assembly dimensions is greater than for most of the previous techniques.

2.3.2.5. Queuing Method

This technique requires the measurement and queuing of some of the items of each component. Then, items from the queues are selected in such a way that they create an assembly with a dimension closest to the desired target [Boy85].

Advantages

1. This technique does not require calculating the bin widths.
2. Significant reduction of the scrap can be achieved.

Disadvantages

1. The assembly variation depends on the ordering of the components. The unfortunate case could happen that only items from the same side of their distributions are measured, queued and matched. In such a situation, short items of one component would be matched with short items of the other component.
2. Additional resources are needed to manage the queues.

2.3.2.6. Ordered Selective Assembling (OSA)

Kwon et al [Kwo09] proposed a different approach, OSA, where all the items of each component are queued in order according to their measured dimensions. Then, items in the same position of their respective queues are selected and matched. The result of this practice is that the smallest item of one component is matched with the smallest item of the other component. This technique is particularly appropriated to solve the mismatch found, for instance, in the problem of shafts and holes (Figure 2-3).

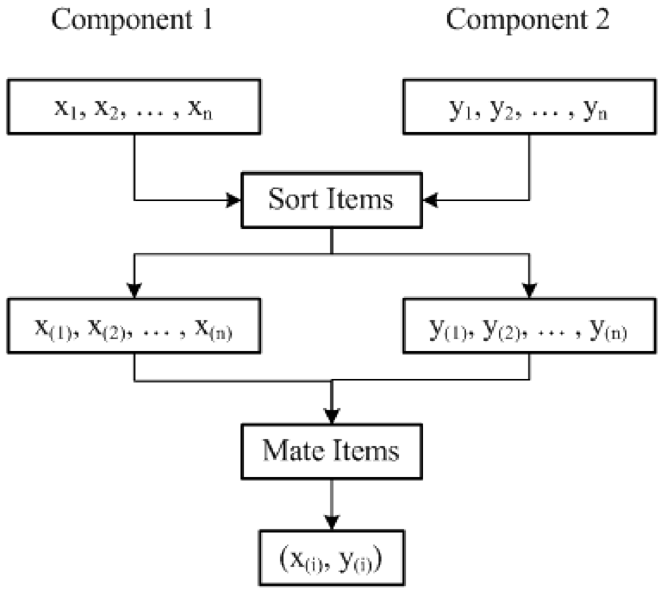


Figure 2-8. Ordered selective assembling [Kwo09].

Advantages

1. This approach might eventually solve the mismatch problem.

Disadvantages

1. Probably in most of the applications, OSA will not help reduce the variation of the resulting assemblies.

2.3.2.7. Selective Assembling based on Process Capability Index (PCI) Tolerances

Zhan et al [Zha98] proposed a different approach that employs PCI-based tolerances to establish a link between the design specifications expressed in the form of the statistical tolerance zone and the process control derived from the application of Statistical Process Control (SPC).

Since the process variation σ^2 and the bias of the process mean μ from the desired target, or mean shift, are the main factors affecting the process quality, this technique suggests the use of two capability indices to allocate tolerances. The first is the Potential Capability Index c_p

$$c_p = \frac{UTL - LTL}{6\sigma} = \frac{t}{3\sigma} \tag{2-13}$$

where UTL is the Upper Tolerance Limit and LTL is the Lower Tolerance Limit. The second is the bias mean ratio k of the process

$$k = \frac{\mu - L}{(UTL - LTL)/2} = \frac{\Delta}{\Delta_0} \tag{2-14}$$

where L is the nominal target and t the tolerance of a given component. These two indices are then combined in one equation using the definition of quality loss, *L(x)*, given by Tagushi.

$$L(x) = \frac{A_0}{(\Delta_0)^2}\left[(\mu - L)^2 + \sigma^2\right] = A_0\left[k^2 + \frac{1}{(3c_p)^2}\right] \tag{2-15}$$

where A_0 represents the cost of one unit. In this way, the definition of the PCI-based tolerance zone is flexible and depends on both the cost and the actual value of c_p. According to Zhan et al [Zha98], the matching degree can be assured already at the stage of design by means of defining flexible PCI-based tolerances. Thus, a posterior selective assembling can be improved significantly.

2.3.3. Adaptive Assembling Techniques

This group of techniques is characterized by the modification of some of the process parameters to achieve a reduction of the variation of the resulting assemblies.

2.3.3.1. Customized Machining

This technique consists on measuring a component item and then machining it or its mate to produce desired assembly dimension.

Advantages
1. Reduction of the assembly variance.
2. Significant reduction of the scrap.

Disadvantages
1. High precision machining might be necessary to achieve the desired level of variation.
2. The additional measurements and machining are time consuming.

2.3.3.2. Dynamic Tolerance Charting

The well-known static tolerance charts are graphical representations of the process plan used to allocate tolerances and to control the tolerance stackup.

Chen et al. [Che97] proposed a dynamic model to allocate tolerances to cuts and to validate the process plan based on actual measurements. The proposed dynamic tolerance charting comprises three elements:

1. dimensional chain identification,
2. optimization model,
3. constraint management.

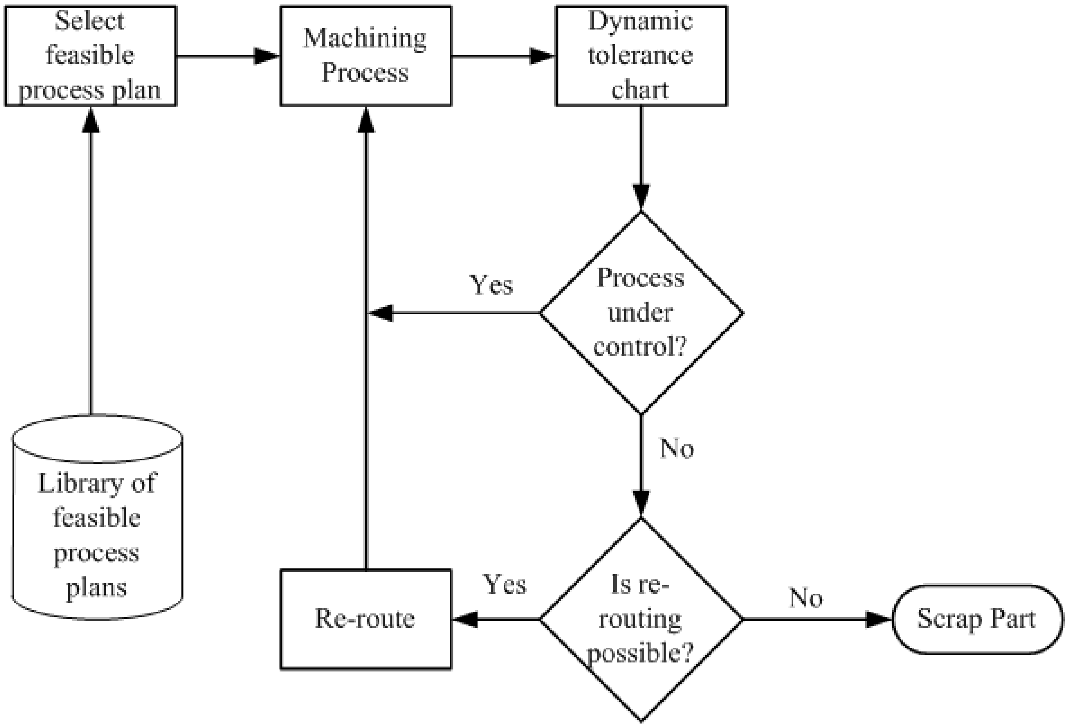


Figure 2-9. Dynamic charting in online process control [Che97].

The idea, assuming a fully automated process, is shown in Figure 2-9. Component items are measured after each machining operation; the data is fed into a dynamic tolerance charting system. The dynamic tolerance chart uses these data to validate the process plan and to reallocate tolerances for subsequent operations. If the process is under control, the machining operations continue, otherwise the possibility of rerouting is explored to change the process plan. If rerouting is not possible, then the part can be scrapped at this stage, thereby saving considerable machining time [Che97].

2.3.4. Combined Assembling Techniques

This group of techniques is characterized by combining some of the features of the selective and the adaptive assembling.

2.3.4.1. Adaptive and Selective Assembling (ASA)

Zocher [Zoc11] defined the Adaptive and Selective Assembling (ASA) as a technology aimed to improve the quality of the products and decrease the cost of quality. The main components of ASA are:

1. the measurement of the probability distribution of quality characteristics,
2. the determination of tolerance groups,
3. the corrections of process parameters,
4. the compensation of quality parameters.

The selective part of ASA involves the assembling of components based on predetermined tolerances groups. The adaptive part of ASA, instead, takes place whenever the process' parameters are adjusted.

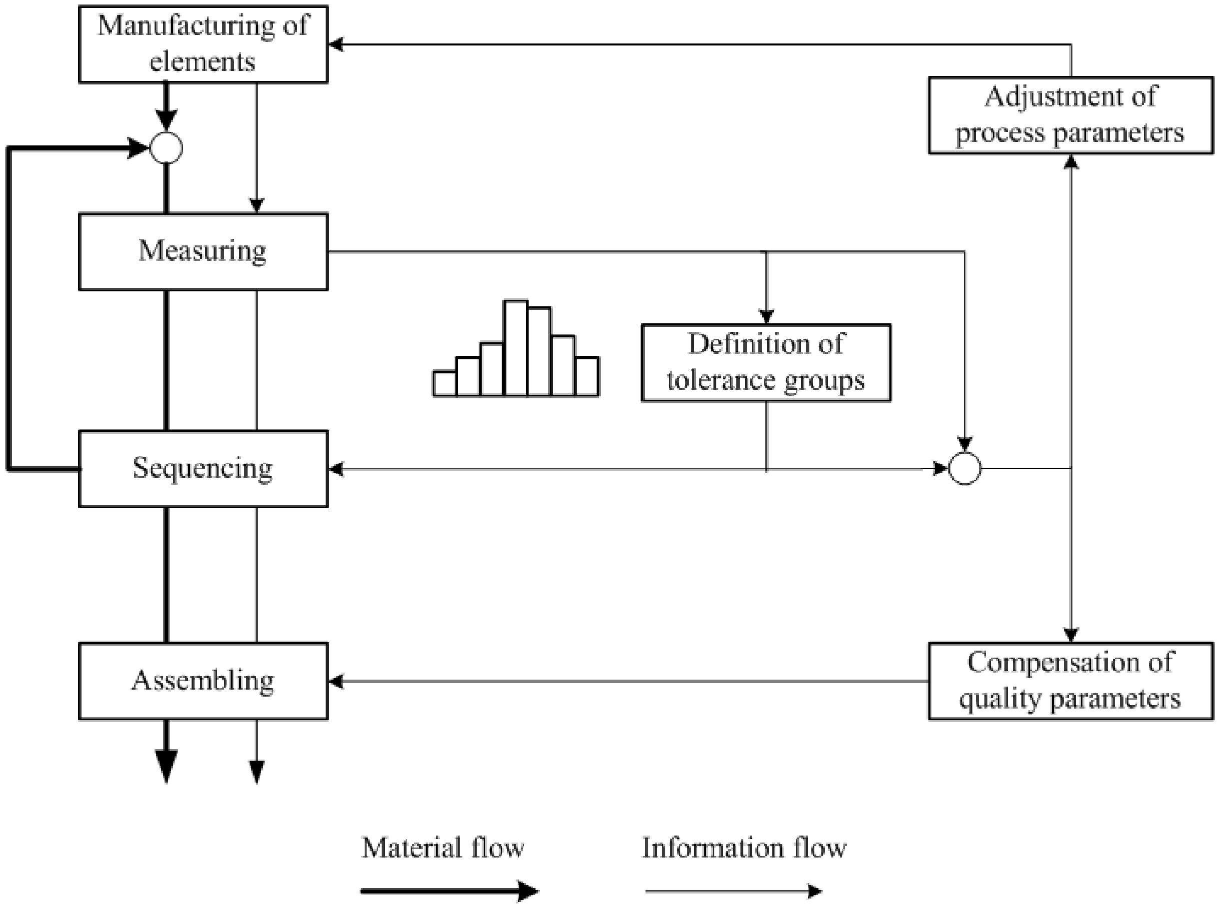


Figure 2-10. System of Adaptive and Selective Assembling [Zoc11].

2.3.4.2. Selective and Adaptive Production Systems (SAPS)

This technique also presents an adaptive and a selective part. While the selective part is characterized by the use of predetermined classified groups to carry the assembling, the adaptive part is characterized by the control and adjustment of the manufacturing processes' parameters. In particular, the adjustment of the target value is defined by the process mean shift [Col12, Kay12-1]. The main difference between ASA and SAPS strives in the scope. SAPS considers all production system elements and not just manufacturing and assembly elements [Kay12-2].

In summary, assembling techniques for low precision processes can be classified in four mayor categories: randomized, selective, adaptive and combined. All the techniques described in this chapter are summarized in Figure 2-11. This is not intended to be the most exhaustive possible list, but to be useful for the purpose of this research.

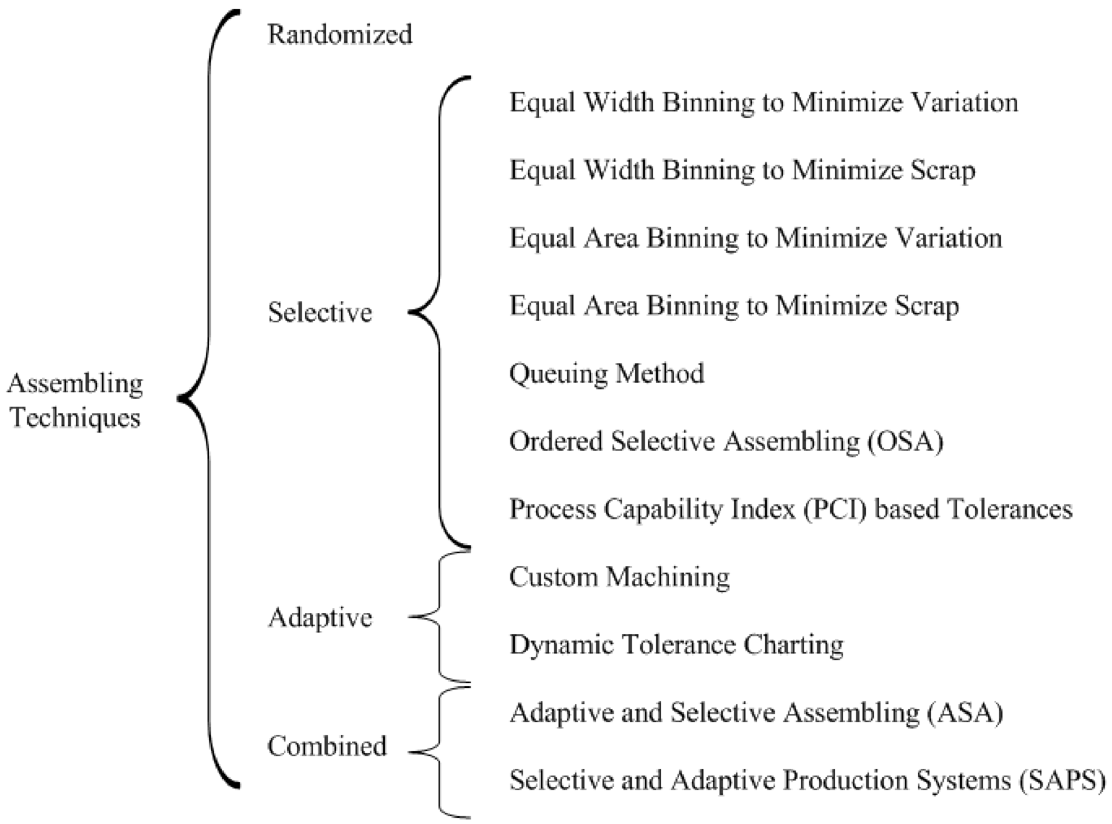


Figure 2-11. Assembling techniques by category.

2.4. Critical Review of the Assembling Techniques

Assuming that every assembling technique was created to satisfy a concrete need of a particular manufacturing process and that it was improved until it finally satisfied its original purpose, or perhaps other from the wide spectrum of existing manufacturing processes (Figure 2.12), it has to be accepted that hardly a specific assembly technique will be the solution for all kind of processes and that it will be always possible to find new applications, advantages and disadvantages for each technique. Kalpakjian et al. [Kal06] present a comprehensive description of a collection of manufacturing processes.

It has been said that the interest of this thesis is set on the assembly techniques oriented to low precision processes that produce high variation components. Therefore, all comparisons will be framed within the proper context and limited to a few parameters of interest not to lose focus.

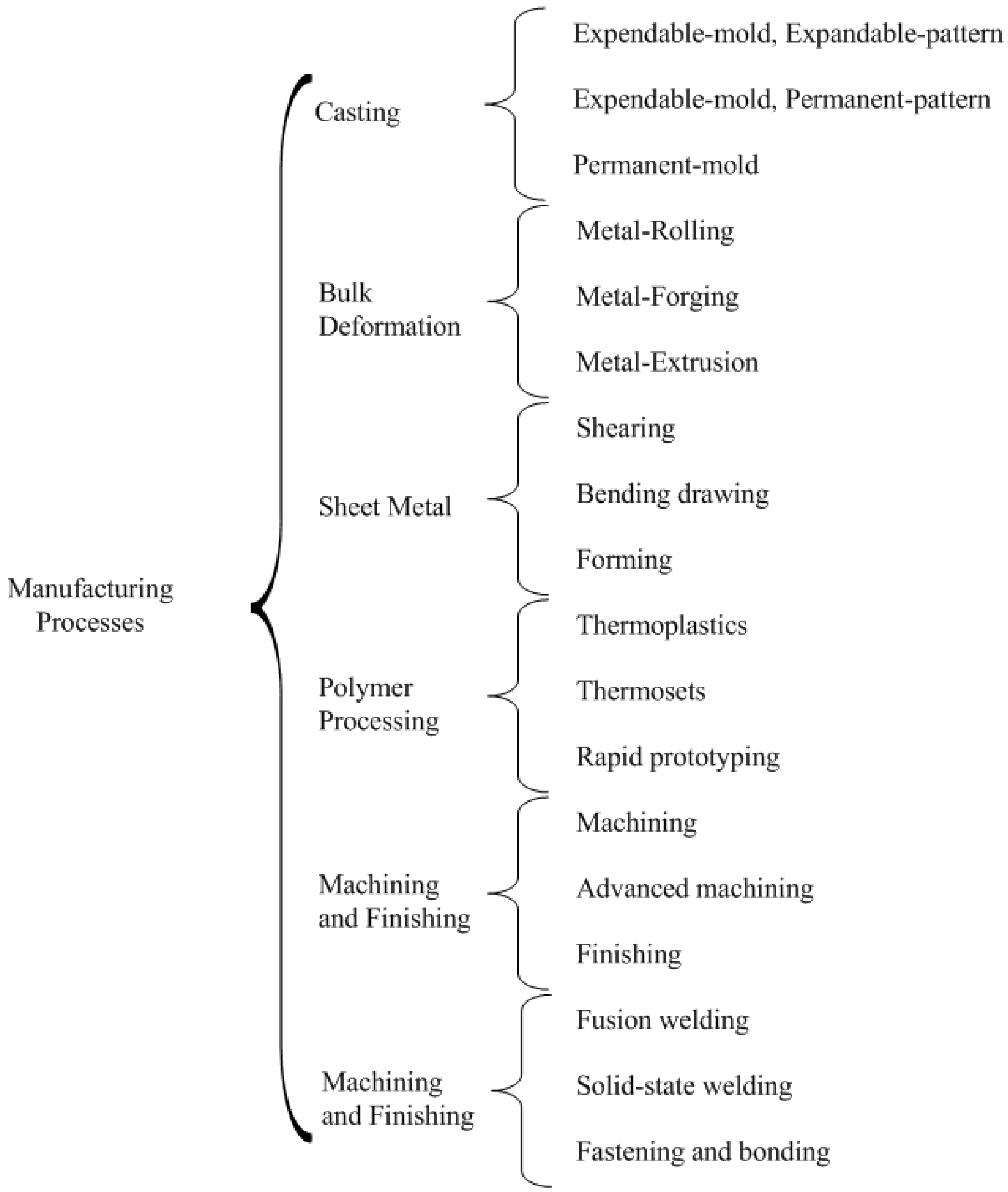


Figure 2-12. Different types of manufacturing processes [Kal06].

2.4.1. Scope of the Discussion

In this thesis the discussion is limited to the problem of assembling high variation components and it is assumed that the characteristics of interest are normally distributed. Even though, in reality, many other distributions can be found.

2.4.2. Objectives of the Assembling Techniques

In general, the assembling techniques presented in this chapter were conceived to help achieving two mayor objectives: the reduction of the process variation and the reduction of the scrap level.

The process variation can be addressed either by means of implementing a selective or an adaptive scheme. While the selective approach helps mating complementary items, the adaptive approach involves the modification of parameters so that adjusted items that compensate the actual deficiencies or excesses can be produced. In both cases, the variation found in the resulting assemblies may be reduced.

The percentage of scrap, of components and assemblies, can be also addressed with a selective or an adaptive scheme. Selective approach may help mating items that belong with bins located at the opposite tails of their distributions so that, small items from the scrap zone of one distribution can be mated to large items from the scrap zone of the other distribution. If the mismatch is relevant, then matching last bins of the same side might be helpful. The adaptive approach, on the other hand, may help defining targets that complement the deviation found in the scrap items in such a way the resulting assemblies fall into the desired tolerance zone.

Even though they serve to similar purposes, the selective and the adaptive scheme are very distinguishable approaches. Selective techniques require the inspection of 100% of the components' items so that the distributions' parameters can be calculated and used to develop the most suitable binning strategy. Bins are designed to minimize either the process variation or the percentage of scrap. Components' items are classified then into predefined categories or bins to be mated afterwards. If the bins are defined a priory, the classification can be performed immediately right after the item inspection. However, in all cases, resources to store and manage the bins need to be allocated (Figure 2-13).

The adaptive approach, on the other hand, does not require an exhaustive inspection of 100% of the components' items. However, a sample of a reasonable size is always necessary to determine the distributions' parameters. In this case, the sample mean is often used to calculate the necessary adjustments to the process parameters, usually, the target of one of the involved components. A special case is the PCI-based tolerance approach in which the tolerance is the subject of the adjustments according to the actual value of the capability indices.

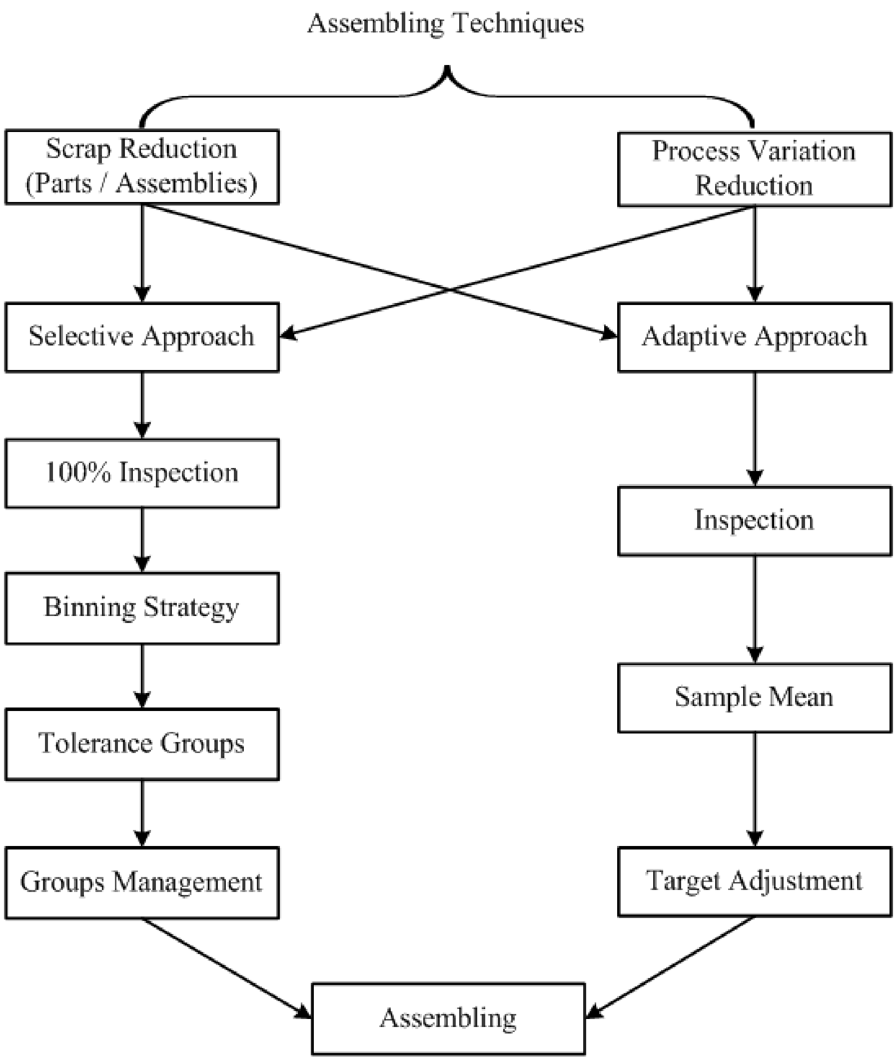


Figure 2-13. Assembling techniques.

2.4.3. Downsides of the Available Assembling Techniques

Depending on the manufacturing process taken as reference the advantages and disadvantages of each technique will vary enormously. Nonetheless, there are a bunch of downsides that are widely valid and, therefore, deserve to be mentioned.

From the list of assembling techniques reviewed in this chapter, it seems evident that the nature of the process variation is not emphasized or simply not considered at all. Logically, in a selective scheme where the inspection of all items can be done after the lots are produced, the evolution of the variation over time is irrelevant. In adaptive schemes, however, some knowledge about the nature of the variation might be helpful to determine proper adjustments.

Since the process variation is the result of the combined influence of different sources that act and evolve as the process advances in time, the variation can be seen as a superposition of different evolving variation forms. In fact, the variation can be separated in two parts: the noise produced by random short-term fluctuations and a long-term component comprising trends and patterns (Figure 2-14).

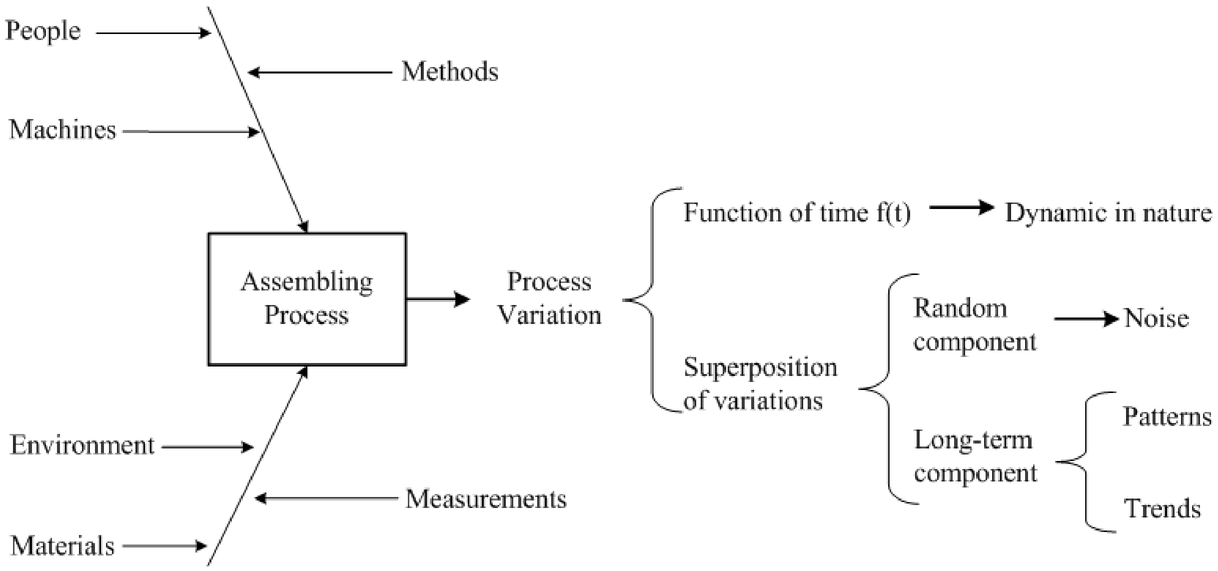


Figure 2-14. Dynamic nature of the process variation.

If the process variation was purely random, then it would not be possible to establish any control loop to monitor such a system because of the randomness of the signal. Thus, depending on the variation range, the process could be either under statistical control or simply not controllable at all. Nonetheless, the mere presence of a detectable long-term component in the variation would offer a good opportunity to establish some sort of control, at least in some degree (Figure 2-15).

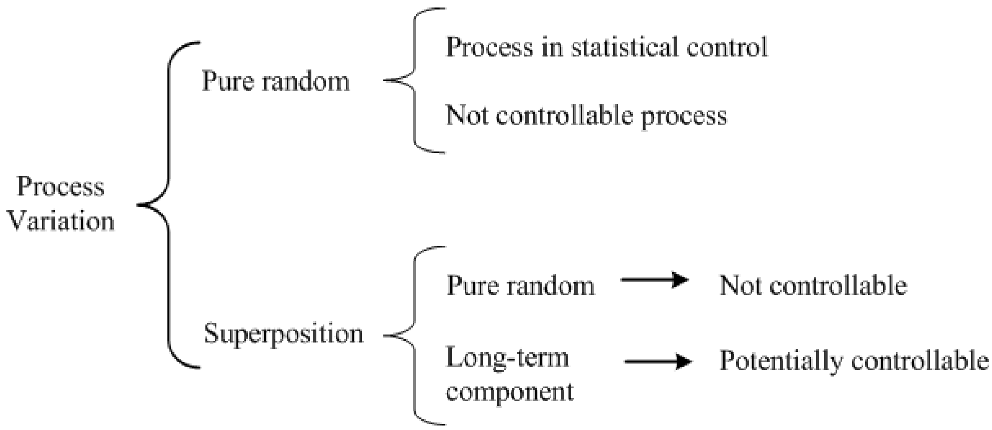


Figure 2-15. Controllability of the process variation.

2.4.3.1. Disadvantages of the Adaptive Assembling

In particular, in adaptive and combined techniques the limitation imposed by the use of the sample mean to determine target adjustments resides in the fact that this estimator does not "have memory", i.e., only the last sample is taken into account. However no historical data about the variation evolution is considered at all. So, it would not be simple to discover the presence of a drift caused by the effect of the tool wear or the progressive material expansion/contraction provoked by changes of temperature. The impact of this practice is rather important because the use of the sample mean impedes to model statistically the controllable component of the variation, and in consequence, to counter it properly.

Another disadvantage of the adaptive schemes is the need of sophisticated equipment to perform in-line measurements and to implement the adjustments in real time while the process is running. If the required adjustments are so small that they can be only performed by high precision equipment, then the initial premise of producing high precision assemblies from low precision processes would not be satisfied.

Finally, the manufacturing process under observation has to be suitable for an adaptive technique. For instance, if the measurements are time consuming and take minutes or even hours, then the determination of the adjustments could be not available to be applied in time.

2.4.3.2. Disadvantages of the Selective Assembling

Even though studied and documented for almost one century, selective assembling techniques have never enjoyed of great popularity.

The first obstacle imposed by this technique is the necessity of implementing a full inspection to cover 100% of the component items in both lots. In contrast to classical statistical control methods, in which the inspection of some samples would be enough to reject or accept the whole lot, in selective schemes even those items that finally will be regarded as scrap have to be measured in some point. Depending on the process and the lot size, the implementation of in-line inspection may require sophisticated equipment. The implementation of off-line inspection, instead, may require additional resources for managing inventories and queues.

Another disadvantage is that none of the binning strategies, at least those presented in this chapter, guarantees the total elimination of the scrap because all of them truncate the area under the probability density function at -3σ and at $+3\sigma$. Even more, in some cases the wider distribution has to be truncated to fit the tighter one. In this case, the higher scrap level in the wider distribution will make necessary some degree of overproduction to end up with enough items to assemble.

2.4.4. Alternative Assembling Technique

In summary, there are no few possibilities to improve the features of the techniques presented in this chapter. Firstly, it is necessary to take advantage of the dynamic nature of the process variation as a function of time. Different alternatives can be analyzed and explored, particularly, concentrating the efforts on that part of the variation that is potentially controllable. Hence, an adaptive technique would be the most suitable approach.

Secondly, the modeling of the variation's evolution over time requires the definition of statistics and estimators with "memory" that are able to keep the trace of the evolution and to take it into account to determine the necessary adjustment in a proper way.

At last, the optimization of the inspection activities and the required resources would increase the flexibility and applicability of an alternative approach. This would be particularly advantageous when an in-line inspection scheme is in place.

The alternative assembling technique has to be focused in three main aspects:

1. Reduction of the process variation.
2. Reduction of the scrap levels.
3. Improvement of the process capability indices.

The reduction of the process variation can be achieved by means of mating component items that complement one another in such a way that the resulting assemblies are close, as much as possible, to the desired target. This not necessarily implies mating small items of one component with a large ones of the other component. Sometimes, it could be necessary to mate component items of similar sizes, for example, in the case of the shaft and holes.

The process variation can be reduced by means of combining an adaptive approach to calculate the right specification adjustments and a selective approach to mate only those items that complement one another.

The improvement of the capability indices can be achieved by means of

1. reducing the process variation, or
2. extending the tolerances, or
3. reducing the mean shift, i.e., the difference between nominal target and the actual mean.

The reduction of the scrap can be realized either by means of extending the tolerances, in the case of the components, or by means of reducing the mean shift and the standard deviation in the case of the resulting assemblies.

A conceptual design of this alternative assembling technique is shown in Figure 2-16. All of these new features are, in some degree, covered by the proposed Statistical Dynamic Specifications Methods (SDSM) and the Statistical Feed-Forward Control Model (SFFCM) which are the central topics of this thesis and that are discussed in detail in Chapter 3.

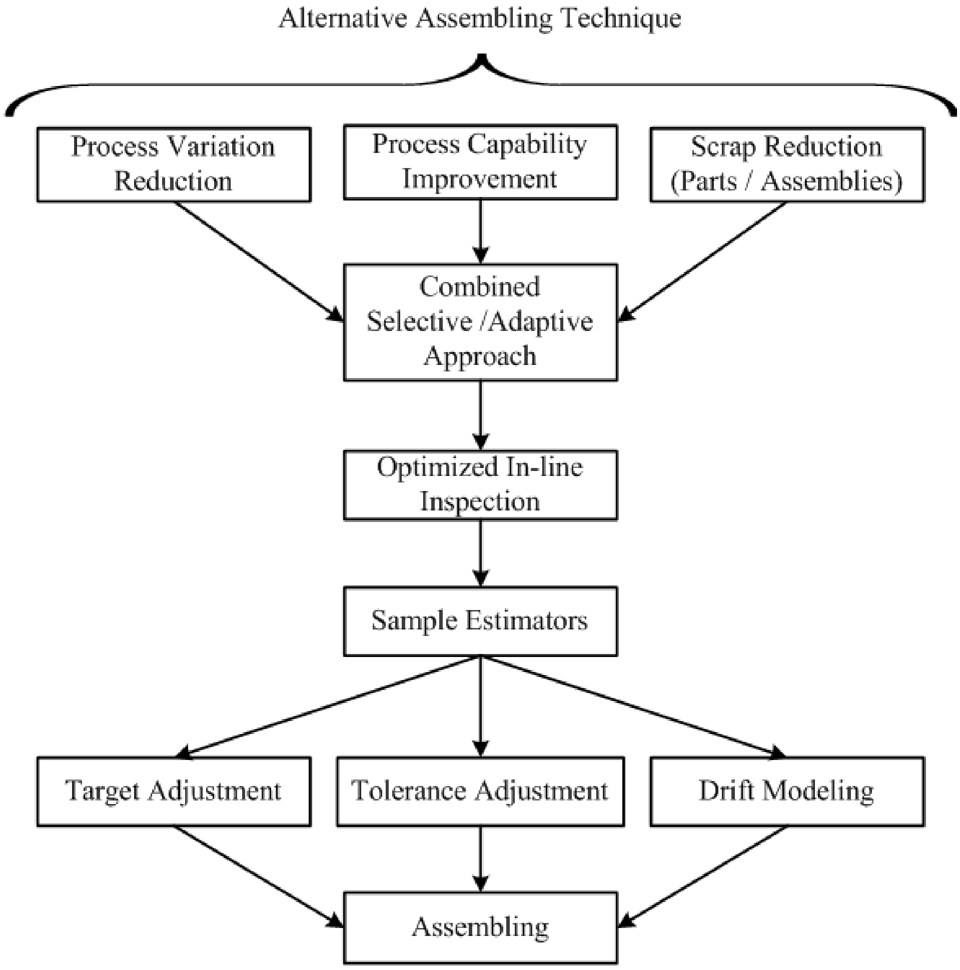


Figure 2-16. Alternative assembling technique.

2.5. Quality

There are two important aspects to consider when deciding on the implementation of a new assembling technique: cost and quality. The latter is the central topic of the following sections.

Quality can be defined as the degree to which a set of inherent characteristics fulfils requirements. In this context, “inherent” means existing in something, especially as a permanent characteristic [ISO 9000-2005 p.7].

Montgomery [Mon09] defines quality as the fitness to use and it is inversely proportional to the process variation. Thus, the quality improvement is the reduction of variability in process and products. According to this definition, quality comprises eight dimensions [Mon09 ch. 1]:

1. Performance,
2. Reliability,
3. Durability,
4. Serviceability,
5. Aesthetics,
6. Features,
7. Perceived quality, and
8. Conformance to standards.

Two important quality-related activities are the quality assurance and the quality control. Whereas quality assurance is focused on prevention to provide confidence that quality requirements will be fulfilled [ISO 9000-2005 p.9]; quality control is focused on detection to maintain standards of quality that prevents and corrects changes in such standards so that the resultant output meets customer needs and expectations [Hoy01 p.654].

2.5.1. Quality Parameters

Quality can be seen as a composite of three parameters: quality of design, quality of conformance and quality of use [Hoy01 p. 31]:

1. Quality of design is the degree to which the design of the product or service satisfies customer needs and expectations.
2. Quality of conformance is the degree to which the product or service conforms to the design standard.
3. Quality of use is the degree to which the user is able to make use the product or service. Products should have a low cost of ownership, be safe and reliable, maintainable in use and easy to use.

2.5.2. Cost of Quality

The cost of quality can be divided into two categories: quality control costs and the quality failure costs. Whereas in the first category are the prevention and the appraisal costs; in the second category the cost of external and internal failure can be found [Rei05 ch.5 pp.140-141].

Table 2-1. Types of Quality Costs [Rei05 ch.5 pp.140-141]

Type of Cost	Description
Prevent	Costs of preparing and implementing a quality plan.
Appraisal	Costs of testing, evaluating, and inspecting quality.
Internal failure	Costs of scrap, rework, and material losses.
External failure	Costs of failure at customer side, including returns, repairs, and recalls.

A detailed description of these costs is given by Park [Par03 p.123].

Table 2-2. Description of the Categories of Quality Costs [Par03 p.123]

Category	Contents
Prevention cost (P-cost)	1. Quality training 2. Process capability studies 3. Vendor surveys 4. Quality planning and design 5. Other prevention expenses
Appraisal cost (A-cost)	1. All kinds of testing and inspection 2. Test equipment 3. Quality audits an reviews 4. Laboratory expenses 5. Other appraisal expenses
Internal failure cost (F-cost)	1. Scrap and rework 2. Design changes 3. Excess inventory cost 4. Material procurement cost 5. Other internal failure expenses
External failure cost (F-cost)	1. After-service and warranty costs 2. Customer complaints visits 3. Returns and recalls 4. Product liability suits 5. Other external failure expenses

2.5.3. Quality Management Systems (QMS)

QMS is the part of the organization's management system that focuses on the achievement of results, in relation to the quality objectives, to satisfy the needs, expectations and requirements of interested parties, as appropriate. The quality objectives complement other objectives of the organization such as those related to growth, funding, profitability, the environment and occupational health and safety [ISO9000-2005 p.6].

2.5.3.1. Total Quality Management (TQM)

TQM can be seen as an organizational effort aimed to improve quality at every level of the organization. It differs from the classic concept of quality because its focus is on serving customers, identifying the causes of quality problems, and building quality into the production process (Figure 2-17). TQM philosophy is the result of combining seven features: customer focus, continuous improvement, employee empowerment, use of quality tools, product design, process management, and managing supplier quality [Rei05 ch.5 p.142].

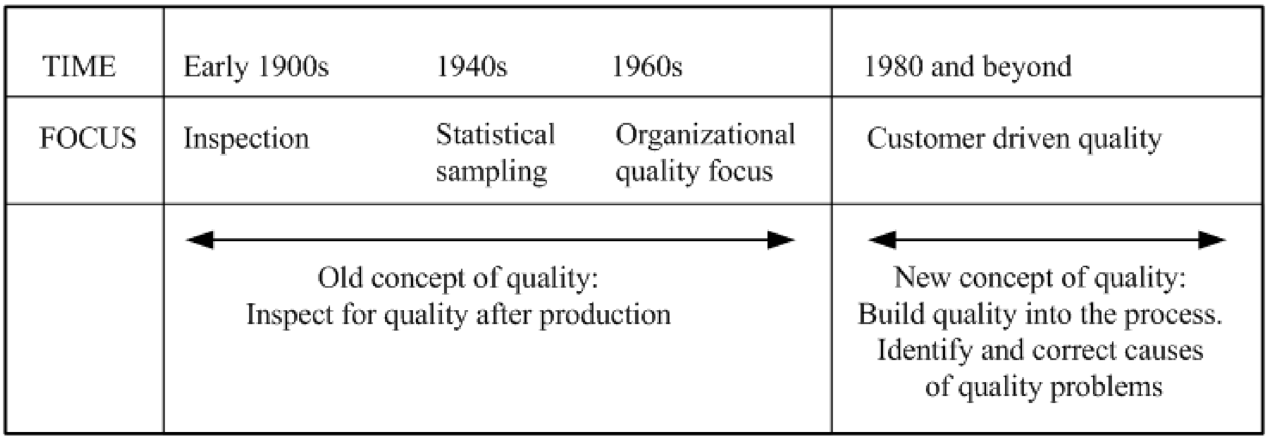


Figure 2-17. Timeline of classical and newer concept of quality [Rei05 ch.5 p.142].

2.5.3.2. Six Sigma

Six Sigma can be seen as a strategic paradigm of management innovation which implies three things: statistical measurement, management strategy and quality culture. It is aimed to improve the quality of process outputs by means of identifying and removing the causes of defects (errors) and minimizing variability in manufacturing and business processes [Par03 p.2].

The term Six Sigma originated from terminology associated with manufacturing. The maturity of a manufacturing process can be described by a sigma rating indicating its yield or the percentage of defect-free products it creates. A Six Sigma process is one in which 99.99966% of the products manufactured are statistically expected to be free of defects. In other words, only 3.4 defects are expected per one million opportunities.

The evolution of the quality management models up to Six Sigma is shown in Figure 2-18.

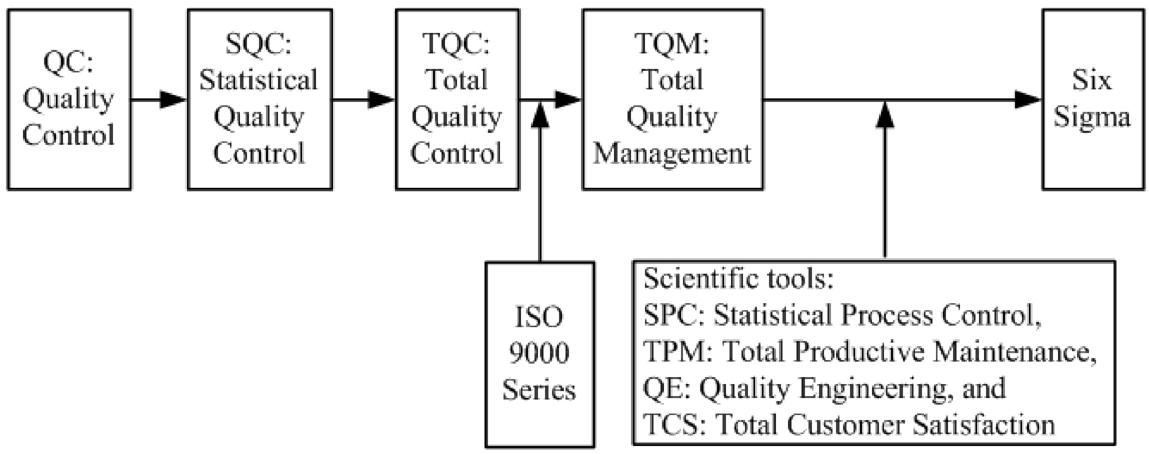


Figure 2-18. Development process of Six Sigma in quality management [Par03 p.3].

The essence of Six Sigma is the integration of four elements (customer, process, manpower and strategy) to provide management innovation. The most important methodology in Six Sigma management is the formalized improvement methodology characterized by the DMAIC (define-measure-analyze-improve-control) process (Figure 2-19).

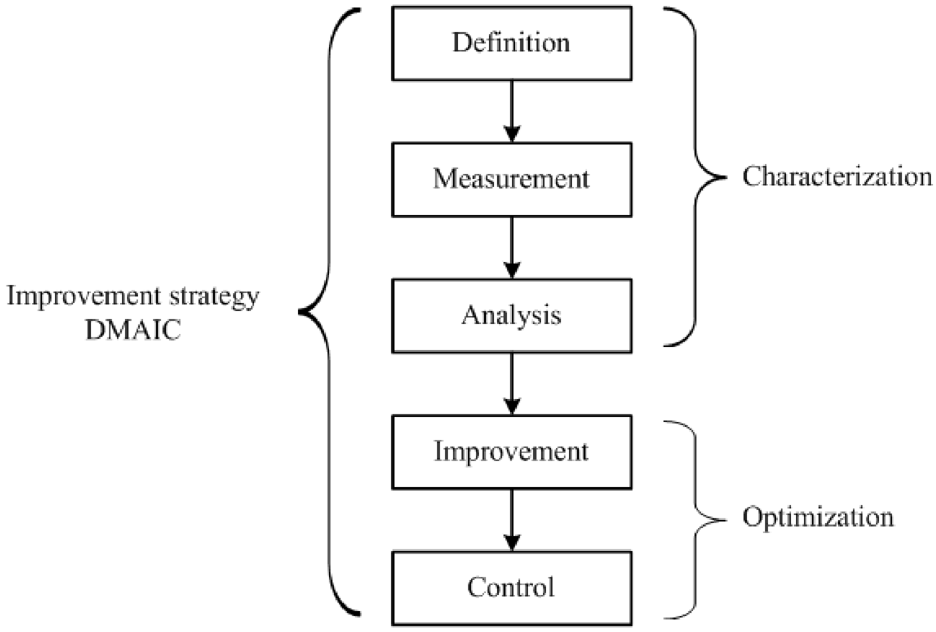


Figure 2-19. Improvement phases [Par03 p.38].

2.6. Chapter Summary

In the first sections of this chapter, the principles of manufacturing were introduced. The emphasis was made on the principle of interchangeability and its relevance in the posterior development of the assembling techniques. Besides the randomized assembling scheme, three approaches were presented: selective, adaptive and combined assembling techniques. All of them were conceived having in mind two mayor objectives: the reduction of the process variation and the reduction of the scrap level. Examples of each approach, their mayor advantages and disadvantages were presented as well.

In the middle section of this chapter, a critical review of the available assembling techniques was given. From the premise of producing low variation assemblies made of high variation components, the mayor downsides of selective and adaptive approaches were exposed. To close the discussion, the gaps and the improvement opportunities found in the reviewed techniques were identified and explained. Finally, the requirements for an alternative assembling technique aimed to reduce the process variation, increment the process capability indices and reduce the scrap were defined.

The final section of this chapter presents a review of the concept of quality. The quality parameters and the costs of quality were presented. At the end, a short overview of quality management techniques, their evolution and the Six Sigma approach are given as well.

3. STATISTICAL FEED-FORWARD CONTROL MODEL

Chapter Highlights

- Presents tolerance stacking methods
- Describes parameters, estimators and properties of normal distributions
- Gives basic notions about Statistical Process Control (SPC)
- Introduces the Statistical Dynamic Specifications Method (SDSM))
- Introduces the Statistical Feed-Forward Control Model (SFFCM)
- Explains the application of SFFCM to multi-component assembling
- Explains the implementation of SFFCM in parallel manufacturing lines
- Introduces an alternative configuration of SFFCM with an external feedback loop

3.1. Introduction

Rather than concentrating the efforts in neutralizing the influence of the sources of variation or implementing selective assembling schemes, this thesis proposes the dynamic management of the component specifications, target and tolerance, and the mating of complementing groups of items as the appropriate approach to follow when assembling high variation components.

The Statistical Dynamic Specifications Method (SDSM) can be seen as a statistical tool that helps determine the right specification adjustments using samples taken from a small group of items produced consecutively during a short-time interval. Whereas, the Statistical Feed-Forward Control Model (SFFCM) can be seen as a monitoring tool that helps counter the effect of the "detectable" long-term component of the variation on the characteristics of interest.

3.1.1. Overview

This chapter gives a deep explanation of the proposed SDSM and SFFCM, their theoretical fundaments, their characteristics and the way in which they interact to give rise to an innovative assembling technique.

Chapter Goals

- Present the theoretical fundaments behind SDSM and SFFCM.
- Introduce the Statistical Dynamic Specifications Method (SDSM)).
- Introduce the Statistical Feed-Forward Control Model (SFFCM).
- Explain the implementation of the proposed SFFCM-based assembling technique in parallel manufacturing schemes.
- Explain the properness of the proposed technique for multi-component assembling tasks.
- Introduce an alternative configuration in which SFFCM is complemented by an external feedback loop.

3.1.2. Background

During the development of SFFCM a wide spectrum of theoretical fundaments were analyzed and applied. Given that assembling techniques have been studied for a long time it is not hard to find abundant literature with exhaustive mathematical analysis that are available to be used, extended and applied in many different ways.

In this section, the fundamentals of the tolerance stacking analysis, the properties of normal distributions and the Statistical Process Control (SPC) are presented to facilitate the understanding of SDSM and SFFCM which will be explained later on.

3.1.2.1. Engineering Tolerance

Tolerance is the total amount a specific dimension is permitted to vary, i.e., the difference between the maximum and minimum limits. In particular, geometric tolerance is the general term applied to the category of tolerances used to control size, form, profile, orientation, location, and runout [ASME-Y14.5-2009 p.7].

3.1.2.2. Tolerance Stack Analysis Methods

There are two mayor approaches to stack tolerances: worst-case analysis and statistical analysis. Buckingham [Buc21, pp.42-43] discussed the importance of the individual component tolerances for the final assembly and proposed some techniques to test linear tolerances. However, it was Rüdenberg [Rud29 p.34] who presented the linear and statistical tolerance stacking formulae in the way they are known today.

In the linear or arithmetic stack tolerance method, also referred as the worst case model, the tolerances assigned to component items of an assembly are determined by arithmetically dividing the assembly tolerance among the individual components of the assembly [ASME-Y14.5-2009 pp.37-38]. Here, it is assumed that the dimensions of the component items may have any value within its tolerance range and the arithmetically stacked tolerances describe the range of all possible variations for the characteristic of interest [Sch95].

$$t_{arith} = \sum_{i=1}^{n} t_i \tag{3-1}$$

In the statistical stack tolerance method, instead, it is assumed that the dimensions of the component items vary randomly according to a normal distribution, centered at the midpoint of the tolerance range and with its ±3σ spread covering the tolerance interval [Sch95]. This statistical method typically leads to tighter assembly tolerances and it is used to increase individual component tolerance and thus, to reduce manufacturing costs. However, it should only be employed where the appropriate statistical process control is implemented [ASME-Y14.5-2009 pp.37-38].

$$t_{stat} = \sqrt{\sum_{i=1}^{n} t_i^2} \tag{3-2}$$

Scholz [Scho95] presents a brief list of tolerance stacking methods that cover some variations and combinations of the linear and statistical methods mentioned above.

3.1.2.2.1. Tolerance and Allowance

Often, the terms allowance and tolerance are incorrectly interchanged in technical papers. Tolerance is the limit of acceptable unintended deviation from a nominal or theoretical dimension. Therefore, a pair of tolerance limits, upper and lower, defines a range within which an actual dimension may fall while still being acceptable. Allowance, instead, is an intentional difference between maximum material limits of mating items.

3.1.2.3. Normal Distribution

Since the proposed SDSM and SFFCM were conceived to deal with lots of items whose characteristic of interest was assumed to be normally distributed, it is worthy to have a look at this probability distribution.

The normal or Gaussian distribution is a continuous probability distribution that has a bell-shaped probability density function (PDF) [NIST/SEMATECH ch.1.3.6.6.1, Oli12 ch.10],

$$f\left(x;\mu,\sigma^2\right) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \tag{3-3}$$

The parameter μ is the mean or expectation, σ^2 is the variance and σ is the standard deviation. The normal distribution is used often as a first approximation to describe random variables that spread around a mean value.

This distribution comes from the central limit theorem which states that the mean of a large number of random variables drawn from the same distribution is distributed approximately normally, regardless of the form of the original distribution.

If μ is equal to 0 and σ is equal to 1, the probability density function in equation (3-3) can rewritten as follows

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} \tag{3-4}$$

This function has to fulfill the following condition:

$$\int_{-\infty}^{\infty} f(x)dx = 1 \tag{3-5}$$

Normal distributions are the result of the exponentiation of a quadratic function

$$f(x) = e^{ax^2+bx+c} \tag{3-6}$$

where a defines the width of the bell curve shape coming from the quadratic function, b defines the location of the central peak of the bell along the x-axis. Nevertheless, instead of a, b, and c, the mean $\mu = -b/2a$ and the variance $\sigma^2 = -1/2a$ are used to describe a normal distribution.

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{3-7}$$

The parameter μ is at the same time the mean, the median and the mode of the normal distribution. The parameter σ^2 describes how spread the distribution is around its mean.

3.1.2.3.1. Properties and Theorems of Normal Distributions

The following properties and theorems provide the theoretical framework of SFFCM. They will be recalled later on.

1. If X is normally distributed with mean μ and variance σ^2, then a linear transform $aX + b$ $\{\forall a, b \in \Re\}$ is also normally distributed.

$$aX + b \sim N\left(a\mu + b, a^2\sigma^2\right) \tag{3-8}$$

2. If X_1, X_2 are two independent normal random variables, with means μ_1, μ_2 and standard deviations σ_1, σ_2, then their linear combination will also be normally distributed [Dun65 ch.10 p.91].

$$aX_1 + bX_2 \sim N\left(a\mu_1 + b\mu_2, a_1^2\sigma_1^2 + b_2^2\sigma_2^2\right) \tag{3-9}$$

3. The normal distribution is infinitely divisible: for a normally distributed X with mean μ and variance σ^2 it is possible to find n independent random variables $\{X_1, \ldots, X_n\}$ each distributed normally with means μ/n and variances σ^2/n such that

$$X_1 + X_2 + \ldots + X_n \sim N\left(\mu, \sigma^2\right) \tag{3-10}$$

4. Cramér's Decomposition Theorem: If X_1 and X_2 are independent and their sum $X_1 + X_2$ is distributed normally, then both X_1 and X_2 must also be normal. A normal distribution is only divisible by other normal distributions [Ros87, Bry05 ch.2 p.29].

5. Bernstein's Theorem: If X and Y are independent and such that $X + Y$ and $X - Y$ are also independent, then both X and Y must necessarily have normal distributions [Bry05 ch.5 p.61].

3.1.2.3.2. Normality Tests

Normality tests are meant to assess the likelihood that a data set $\{x_1, \ldots, x_n\}$ comes from a normal distribution. Whereas the null hypothesis H_0 is that the observations are distributed normally with some mean μ and variance σ^2; the alternative hypothesis H_a is that the distribution is arbitrary. Tests are commonly classified in three mayor categories:

1. Visual tests such as Quantile-Quantile Plot (Q-Q plot), the P-P plot, the Wilk–Shapiro test and the Normal Probability plot [NIST/SEMATECH ch.7.2.1.3].
2. Moment tests such as D'Agostino's K-squared test and the Jarque–Bera test.
3. Empirical distribution function tests such as Kolmogorov–Smirnov test and the Anderson–Darling test [NIST/SEMATECH ch.1.3.5].

3.1.2.3.3. Estimation of Parameters

The approximate values of the parameters μ and σ^2 of a normally distributed population $N(\mu,\sigma^2)$ from a sample $\{x_1, \ldots, x_n\}$ can be found with the help of the maximum likelihood method, which requires maximization of the log-likelihood function [Oli12 ch.10 pp.366-367].

$$\ln \ell(\mu,\sigma^2) = \sum_{i=1}^{n} \ln f\left(x_i;\mu,\sigma^2\right) = -\frac{n}{2}\ln(2\pi) - \frac{n}{2}\ln\sigma^2 - \frac{1}{2\sigma^2}\sum_{i=1}^{n}(x_i-\mu)^2 \tag{3-11}$$

The estimates can be found after solving the system of equations obtained from the derivatives of the equation (3-11) with respect to μ and σ^2.

$$\hat{\mu} = \bar{x} \equiv \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3-12}$$

$$\hat{\sigma}^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2 \tag{3-13}$$

The estimator $\hat{\mu}$ is called the sample mean. In finite samples it is normally distributed.

$$\hat{\mu} \sim N(\mu, \sigma^2/n) \tag{3-14}$$

The estimator $\hat{\sigma}^2$ is called the sample variance. In practice, the estimator s^2 is often used instead of the $\hat{\sigma}^2$ and also called the sample variance.

$$s^2 = \frac{n}{n-1}\hat{\sigma}^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 \tag{3-15}$$

For large vales of n, the difference between s^2 and $\hat{\sigma}^2$ becomes negligibly. In finite samples however, s^2 is preferable because it is an unbiased estimator of σ^2, whereas $\hat{\sigma}^2$ is biased. Even though Lehmann–Scheffé Theorem guarantees that the estimator s^2 is the best of all unbiased estimators [Oli12, ch.4 p.126, Tou95 ch.3 p.58], the biased estimator $\hat{\sigma}^2$ gives rise to smaller mean squared error (MSE) than s^2. In finite samples both s^2 and $\hat{\sigma}^2$ have chi-squared distribution with $(n-1)$ degrees of freedom [Ost75 ch.5 p.99].

$$s^2 \sim \frac{\sigma^2}{n-1}\cdot\chi^2_{n-1} \tag{3-16}$$

$$\hat{\sigma}^2 \sim \frac{\sigma^2}{n}\cdot\chi^2_{n-1} \tag{3-17}$$

Cochran's Theorem states that the sample mean $\hat{\mu}$ and the sample variance s^2 of a normal distribution are independent [And80 p.3]. A reverse theorem states that if in a sample the sample mean $\hat{\mu}$ and sample variance s are independent, then the sample must have come from the normal distribution. This fact can be used to construct the t-statistic [Ost75 ch.5 p.94]:

$$t = \frac{\hat{\mu} - \mu}{s/\sqrt{n}} \sim t_{n-1} \tag{3-18}$$

where t has the Student's t-distribution with (n-1) degrees of freedom. The confidence interval for μ, with unknown variance, can be constructed by means of inverting the distribution of this t-statistic [Ost75 ch.5 p.94]. In the same way, the confidence interval for σ^2 can be constructed by means of inverting the χ^2 distribution of the statistic s^2 [Ost75 ch.5 p.99].

$$\mu \in \left[\hat{\mu} - t_{n-1,(1-\alpha/2)}\frac{s}{\sqrt{n}}, \hat{\mu} + t_{n-1,1-\alpha/2}\frac{s}{\sqrt{n}}\right] \tag{3-19}$$

$$\sigma^2 \in \left[\frac{(n-1)s^2}{\chi^2_{n-1,1-\alpha/2}}, \frac{(n-1)s^2}{\chi^2_{n-1,\alpha/2}} \right] \tag{3-20}$$

where $t_{k,p}$ and $\chi^2_{k,p}$ are the p-th quantiles of the corresponding *t*- and χ^2-distributions. These confidence intervals are of the level (1−α), i.e., the true values μ and σ^2 fall outside of these intervals with probability α. In practice, α = 5% is usually taken, resulting in the 95% confidence intervals. These numbers will be used later on.

The formulae above are derived from the asymptotic distributions of $\hat{\mu}$ and s^2 and are valid for large values of n.

3.1.2.4. Statistical Models

A statistical model is a probability distribution constructed to enable inferences to be drawn or decisions made from data. The key feature of a statistical model is that variability is represented using probability distributions. Typically, statistical models have to accommodate both random and systematic variation [Dav03 ch.1 p.1].

A more formal definition given by McCullagh [Mcc02 p.1225] states that a statistical model is a set of probability distributions on the sample space *S* and a parameterized statistical model as a parameter set Θ together with a function P: Θ →*P* (*S*), which assigns to each parameter point $\theta \in \Theta$ a probability distribution P_θ on *S*. Here *P* (*S*) is the set of all probability distributions on *S*.

Commonly in statistical modeling, and in process modeling, polynomial and rational functions are used as an empirical technique for curve fitting. Models consist of two elements: architecture and parameters, being the polynomial regression one of the most commonly used. There, the architecture is a polynomial of a given degree and the parameters are the coefficients of that polynomial. Once the architecture has been defined, the model can be fitted with the appropriate values of the parameters using different techniques like least squares.

To decide about the properness of a given model, two criteria have to be considered: the ability to explain the observed data and the ability to generalize to the whole population [Kus06 ch.2 p.12].

3.1.2.4.1. The Bias-Variance Trade-off for an Estimator

The relevance of the bias-variance trade-off or "bias-variance dilemma" strives in that it might lead to over-fitting or to under-fitting. If a data-generating process is composed of a deterministic and a random component, the over-fitting may occur when the systematic component is flexible enough to make a maximum likelihood estimate misinterpret the random fluctuation as systematic variation. However, if a model makes too simplistic assumptions, systematic variation can be interpreted as random fluctuation which is known as under-fitting [Kus06 ch.2 p.12].

The bias-variance trade-off implies that the introduction of certain amount of bias into an otherwise unbiased estimator $\hat{\theta}$ of a parameter θ may improve its performance, which can be measured by its Mean Square Error (MSE) [AIACCESS-2011].

$$MSE\left(\hat{\theta}\right) = E\left[\left(\hat{\theta} - \theta\right)^2\right] \tag{3-21}$$

The MSE is equal to the sum of the variance and the squared bias of the estimator.

$$MSE\left(\hat{\theta}\right) = Var\left(\hat{\theta}\right) + \left(Bias\left(\hat{\theta}, \theta\right)\right)^2 \tag{3-22}$$

Although the lack of bias may be considered good, only a proper trade-off between the bias of the estimator and its variance might lead to the minimum value of the MSE. This means that the introduction of a given amount of bias into an unbiased estimator might give rise to a reduction of its variance so that the performance of the estimator could be improved.

A polynomial of low degree may not be flexible enough to describe well a set of highly non-linear data. Indeed, the line of a first degree polynomial would be usually far from the data, producing both large errors and highly biased predictions. However, the model would have a low variance because the prediction depends barely on the specific sample selected to construct the model [AIACCESS-2011].

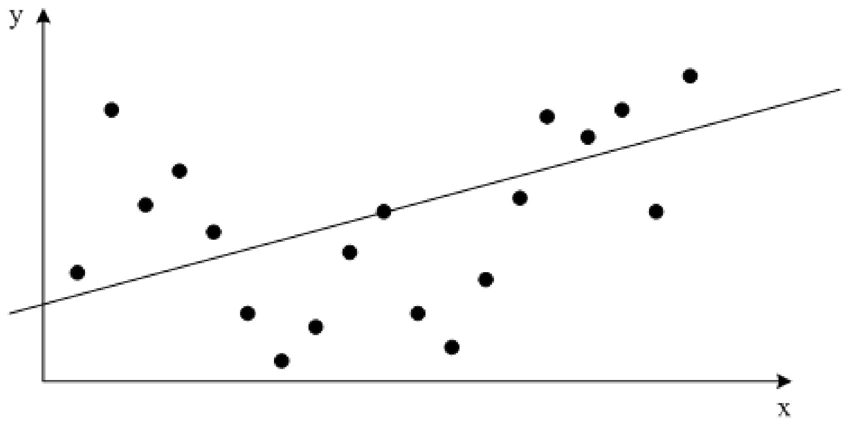


Figure 3-1. Modeling based on a polynomial of first degree [AIACCESS-2011].

With a high degree polynomial, instead, it is possible to generate a curve that might be so sensitive to particular samples that every particular sample could produce a model completely different.

Even though a high degree polynomial model may make predictions with large variance, the curve line now would be closer to the data and since the predictions are less biased, the quadratic error would be lower. This model will have a good performance with previous data but it will probably perform poorly on new data. That is the reason why a good trade-off between bias and variation is the best choice [AIACCESS-2011].

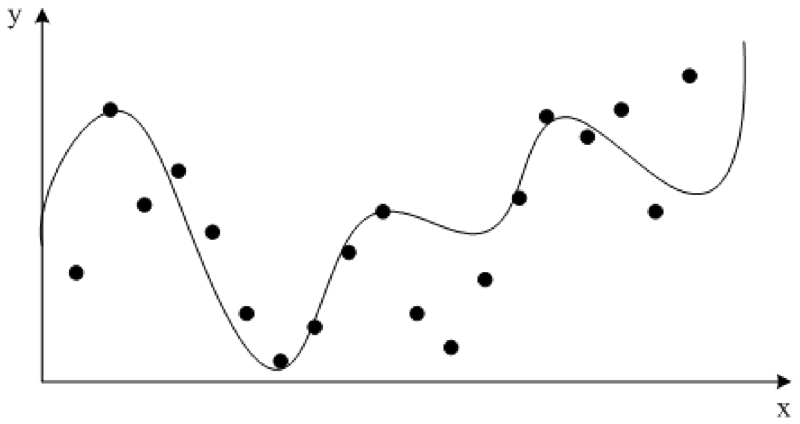


Figure 3-2. Modeling based on a polynomial of high degree [AIACCESS-2011].

3.1.2.5. Sampling Methods

Sampling is the selection of a subset of individuals from a population to estimate its parameters. Since the success in quality control depends greatly on how the samples are drawn, a number of different approaches have been developed through the years [Bur79 ch.8 p.181, Ost75 ch.3 p.52, Wal65 ch.13 p.207].

The most basic method is the simple random sampling in which each individual of the population has an equal probability of selection. The weakness of this method is the chance of “sampling error” due to the randomness of the selection itself that may give rise to a sample that is not representative of the whole population.

An alternative method is the systematic sampling. It requires that the population is arranged according to some criterion. Then, individuals are drawn at regular intervals. Only the first element is taken randomly, the other selections are made every *k-th* individuals to complete the sample. This method is especially vulnerable to periodicities and especially when the period is a multiple of the interval applied.

A different approach is offered by the stratified sampling. Here, the population is characterized by distinguishable categories so that the sample can be organized into separate "strata" or levels. Each stratum is then sampled as an independent subpopulation from which individual elements can be randomly selected. It can be argued that the stratified sampling has some benefits. However, its inherent complexity is the adequate identification of the strata.

3.1.2.5.1. Sample Size

There are several reasons why it is desirable to use a sample from a population rather than inspecting all the individuals. Saving time, money and labor are good reasons but sampling is particularly relevant when the inspection tests are destructive [Bur79 ch.9 p.223]. One of the most important decisions to make before sampling is the number of individuals that should be drawn from a given population. This process will, probably, require additional information and the acceptance of several assumptions [NIST/SEMATECH ch.7].

For a given sample, since the normal distribution curve extends from minus infinity to plus infinity, it is not possible to guarantee that the sample mean $\bar{x}$ is certain to lie between the given limits µ-L and µ+L. It is possible, nevertheless, to make the probability that $\bar{x}$ lies between these limits as large as desired. In practice, this probability is commonly set at 95% or 99%. A 95% probability means that there is a 95% chance that $\bar{x}$ lies between the limits $\mu - 1.96\sigma/\sqrt{n}$ and $\mu + 1.96\sigma/\sqrt{n}$. Thus, the required sample size *n* can be now found readily [Sne67 ch.2 p.58].

$$n = \left(\frac{1.96\sigma}{L}\right)^2 \tag{3-23}$$

Equation (3-23) requires prior knowledge of standard deviation *σ*, although the sample has not yet been drawn. However, in practice, the value may be guessed from previous work on this or from similar populations [Sne67 ch.2 p.58].

When the population mean is unknown, the sample size required for any experiment will depend on different factors:

1. The risk of rejecting a true hypothesis (value of α),
2. The risk of accepting a false null hypothesis when a particular value of the alternative hypothesis is true (value of β),
3. The value of the population standard deviation.

Larger sample sizes generally lead to increased precision when estimating unknown parameters. However, the increase in accuracy for larger sample sizes may be minimal, or even non-existent as a result of the presence of systematic errors or strong dependence in the data.

3.1.2.6. Statistical Process Control (SPC)

Statistical Process Control can be considered as one of three mayor categories of the Statistica1 Quality Control (SQC). The other two are the Descriptive Statistics and the Acceptance Sampling [Rei05 ch.6 p.176].

1. Descriptive Statistics are used to describe quality characteristics and relationships. Included are statistics such as the mean, the standard deviation, the range, and a measure of the distribution of data.

2. Acceptance Sampling is the process of randomly inspecting a sample of items and deciding whether to accept the entire lot based on the results.

According to Reid et al. [Rei05 ch.6 p.173], SPC is a statistical tool that involves inspecting a random sample of items and deciding whether the characteristics of the whole lot fall within a predetermined range. Different from alternative methods, such as inspection, one of the most important advantages of SPC is the emphasis on early detection and prevention of problems, rather than the correcting them after they have occurred. Hence, post-manufacturing inspection can be minimized.

SPC makes possible to examine in detail those parts of the process that may conceal sources of variation so that they can be quantified numerically to determine appropriate corrections. SPC counts on several types of control charts to quantify the variation. Usually control charts are divided in two groups: variables and attributes. While a control chart for variables is used to monitor characteristics that can be measured and have a continuum of values; a control chart for attributes is used to monitor characteristics that have discrete values and can be counted [Rei05 ch.6 p.178].

Pfeifer [Pfe02 ch.5] describes some of the most commonly used SPC procedures. Among them, continuous random sampling, Shewart quality control charts, quality control chart with memory and several capability indices.

In traditional control charts only the most recently inspected samples are considered to make a decision about a correction. Modern control charts, like the KUSUM-mean value chart, take into account the historical data obtained from previous samples as well. The advantage is the higher sensitive reaction of the control functions to disturbances [Pfe02 ch.5 p.376].

3.1.2.6.1. Process in Statistical Control

In the context of SPC, a process is said to be in statistical control when its measured variation remains within known limits. If the variation is excessive, several activities may be performed to identify the sources and to minimize their influence. Useful tools are the Ishikawa diagrams, design of experiments and Pareto charts. Some portion of the variation, however, will always remain.

Toutenburg [Tou95 ch.1 p.8] states that, in experimental work, there are two main sources of uncontrolled variability. These are given by the pure experimental error and a measurement error in which possible interactions are also subsumed. An experimental error is the variability of a response variable under exactly the same experimental conditions. Measurement errors, instead, describe the variability of a response if repeated measurements are taken.

3.1.2.6.2. Process Capability

It is often required to compare the output of a stable process with the process specifications to make a statement about how well the process meets specifications. The comparison is made by forming the ratio of the spread between the process specifications to the spread of the process values, as measured by six process standard deviation units. A capable process is one where almost all the measurements fall inside the specification limits [NIST/SEMATECH ch.6.1.6].

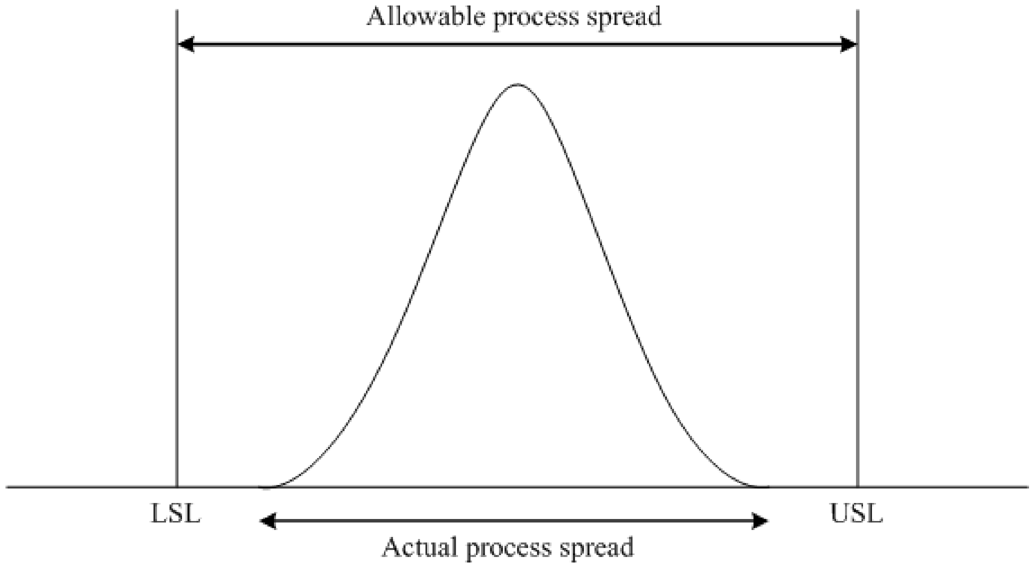


Figure 3-3. Capable process [NIST/SEMATECH ch.6.1.6].

There are different statistics that can be used to measure the capability of a process: the potential capability index c_p , the actual capability index c_{pk} , and the so-called Tagushi capability index c_{pm}. In general, these indices estimates are valid only if the sample size used is 'large enough', meaning, at least 50 independent data values [NIST/SEMATECH ch.6.1.6].

The c_p , c_{pk} , and c_{pm} statistics assume that the population of data values is normally distributed. Assuming a two-sided specification, if μ and σ are the mean and standard deviation, respectively, of the normal data and USL, LSL, and T are the upper and lower specification limits and the target value, respectively, then the population capability indices are defined as follows:

$$c_p = \frac{USL - LSL}{6\sigma} \tag{3-24}$$

$$c_{pk} = \min\left\{\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right\} \tag{3-25}$$

$$c_{pm} = \frac{USL - LSL}{6\sqrt{\sigma^2 + (\mu - T)^2}} \tag{3-26}$$

The corresponding sample estimators are:

$$\hat{c}_p = \frac{USL - LSL}{6s} \tag{3-27}$$

$$\hat{c}_{pk} = \min\left\{\frac{USL - \bar{x}}{3s}, \frac{\bar{x} - LSL}{3s}\right\} \tag{3-28}$$

$$\hat{c}_{pm} = \frac{USL - LSL}{6\sqrt{s^2 + (\bar{x} - T)^2}} \tag{3-29}$$

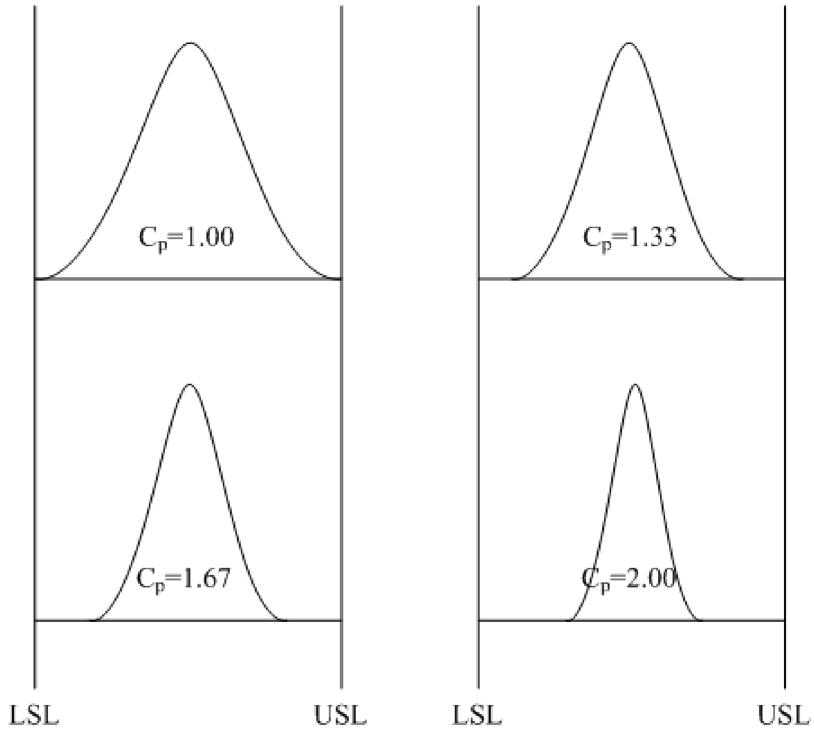


Figure 3-4. Value of the c_p statistic for different distributions [NIST/SEMATECH ch.6.1.6].

A process is regarded as capable if it exhibits a potential capability index c_p equal or higher than 1.33. Additionally, it can be called a controlled process if the actual capability index has a comparable value [Pfe02 ch.5 pp.389-390]. Assuming a distribution centered at μ, the plots in Figure 3-4 can be expressed numerically (Table 3-1).

Table 3-1. Value of c_p for Different Distributions [NIST/SEMATECH ch.6.1.6]

	USL-LSL			
	6σ	8σ	10σ	12σ
c_p	1.00	1.33	1.66	2.00
Rejects	0.27%	64 ppm (*)	0.6 ppm (*)	2 ppb (*)
% of specification used	100	75	60	50

(*) ppm = parts per million, ppb = parts per billion

3.1.2.7. Control Theory

Control theory deals with the behavior of dynamical systems with inputs and outputs. If the system output needs to follow a certain reference (input) over time, a controller manipulates the inputs to produce the desired effect on the output.

3.1.2.7.1. Closed-Loop Controller

A closed-loop controller uses feedback to control the output of a dynamical system. The input has an effect on the output, which is measured with sensors and processed by the controller; the resulting control signal is used as input to the process to close the loop. The main advantages of feedback controllers are:

1. Stable performance even in the presence of uncertainties.
2. Unstable processes can be stabilized.
3. Reduced sensitivity to parameter variations.

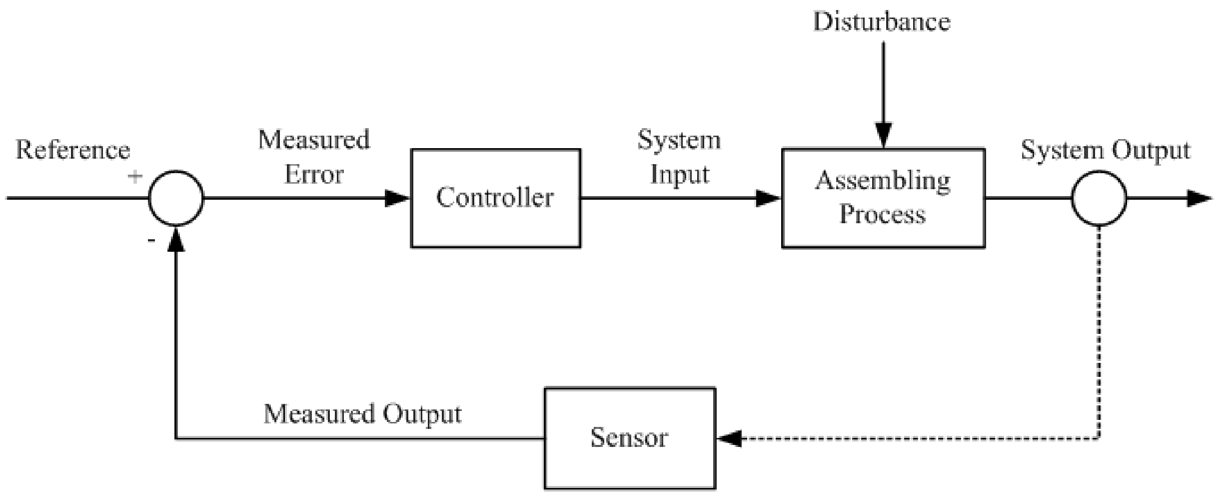


Figure 3-5. Single loop feedback-system [Oga98 ch.3 p.65].

The most used feedback control design is the Proportional-Integral-Derivative (PID) controller [Ast06 ch.2 pp.64-73]:

$$u(t) = K_P e(t) + K_I \int e(t)dt + K_D \frac{d}{dt} e(t) \tag{3-30}$$

where *u(t)* is the control signal sent to the system, *y(t)* is the measured output and *r(t)* is the desired output, and e*(t)* is the tracking error

$$e(t) = r(t) - y(t) \tag{3-31}$$

The control is carried out by means of adjusting the parameters K_P , K_I , and K_D , without specific knowledge of a system model. Laplace transformation turns equation (3-30) into:

$$u(s) = K_P e(s) + K_I \frac{1}{s} e(s) + K_D s e(s) \tag{3-32}$$

$$u(s) = \left(K_P + K_I \frac{1}{s} + K_D s \right) e(s) \tag{3-33}$$

From equation (3-33), the transfer function can be defined as

$$C(s) = \left(K_P + K_I \frac{1}{s} + K_D s \right) \tag{3-34}$$

3.1.2.7.2. Feed-Forward Loop

Different from feedback schemes where the reaction is taking into account to feed the system, a feed-forward design introduces a controlling signal from an external source so that the response is somehow defined *a priori*, regardless of the reaction [Ble03 ch.2 p.84].

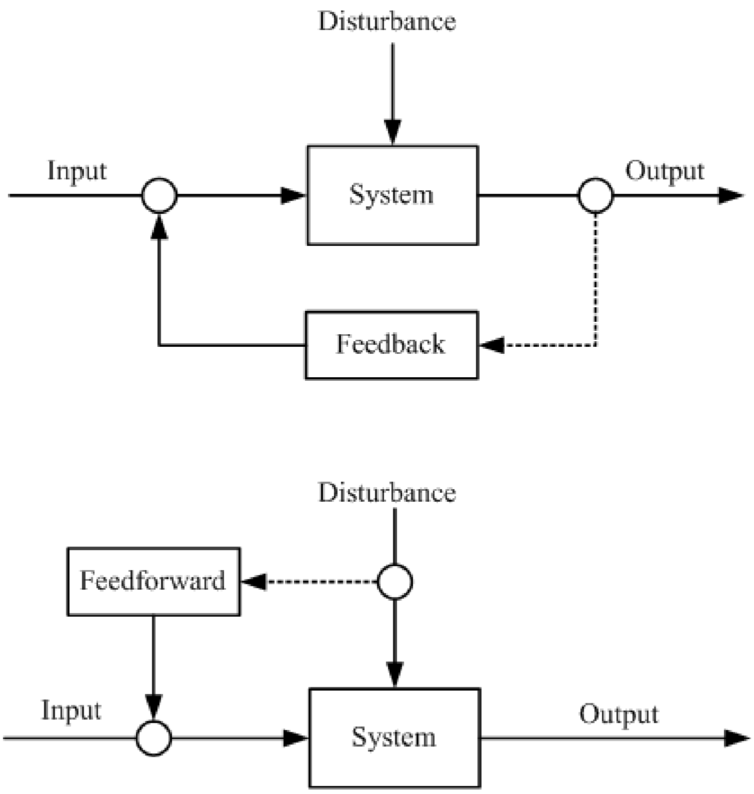


Figure 3-6. Conceptual feedback loop (top) and feed-forward loop (bottom).

3.1.2.7.3. Lyapunov Stability

According to Lyapunov stability criteria, a linear system that takes an input is called bounded-input bounded-output (BIBO) stable if for any bounded input corresponds a bounded output [Mur94 ch.4 pp.44]. This can be formally defined as follows:

The equilibrium point $x^*=0$ of $\{\dot{x}=f(x,t)\ \ x(t_0)=x_0\ ,x\in\Re^n\}$ is stable (in the sense of Lyapunov) at $t=t_0$ if for any $\varepsilon>0$ there exist a $\delta(t_0,\varepsilon)>0$ such that

$$\|x(t_0)\|<\delta\Rightarrow\|x(t)\|<\varepsilon,\forall t\geq t_0 \tag{3-35}$$

3.2. Statistical Dynamic Specifications Method (SDSM)

SDSM comprises a collection of steps that help determine adjustments to nominal targets and to manage the allocation of dimensional tolerances of the components of an assembly.

Whereas adjusted component targets might force the meeting of the assembly nominal target, adjusted extended tolerances might allow items' dimension fluctuate in a wider band. This is especially interesting because, seen from a different perspective, process capability indices can be improved without any re-engineering but as a direct consequence of the tolerance range enlargement [Her11-1].

3.2.1. Dimensional Variation

Let L_{assy} and t_{assy} be the target and tolerance of a given assembly whose two inner components' specifications have been set to L_j and t_j (Figure 3-7).

$$L_{assy} = L_1 + L_2 \quad (3\text{-}36)$$

$$t_{assy} = \sqrt{t_1^2 + t_2^2} \quad (3\text{-}37)$$

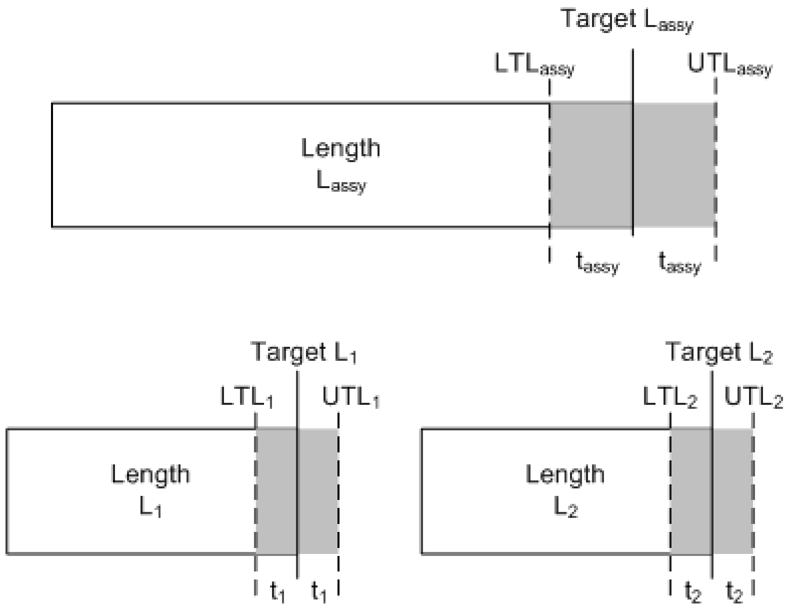


Figure 3-7. Nominal targets and tolerances.

Let the variation of the items' length of Component 1 be formed by the superposition of random noise and a long-term component or drift (Figure 3-8).

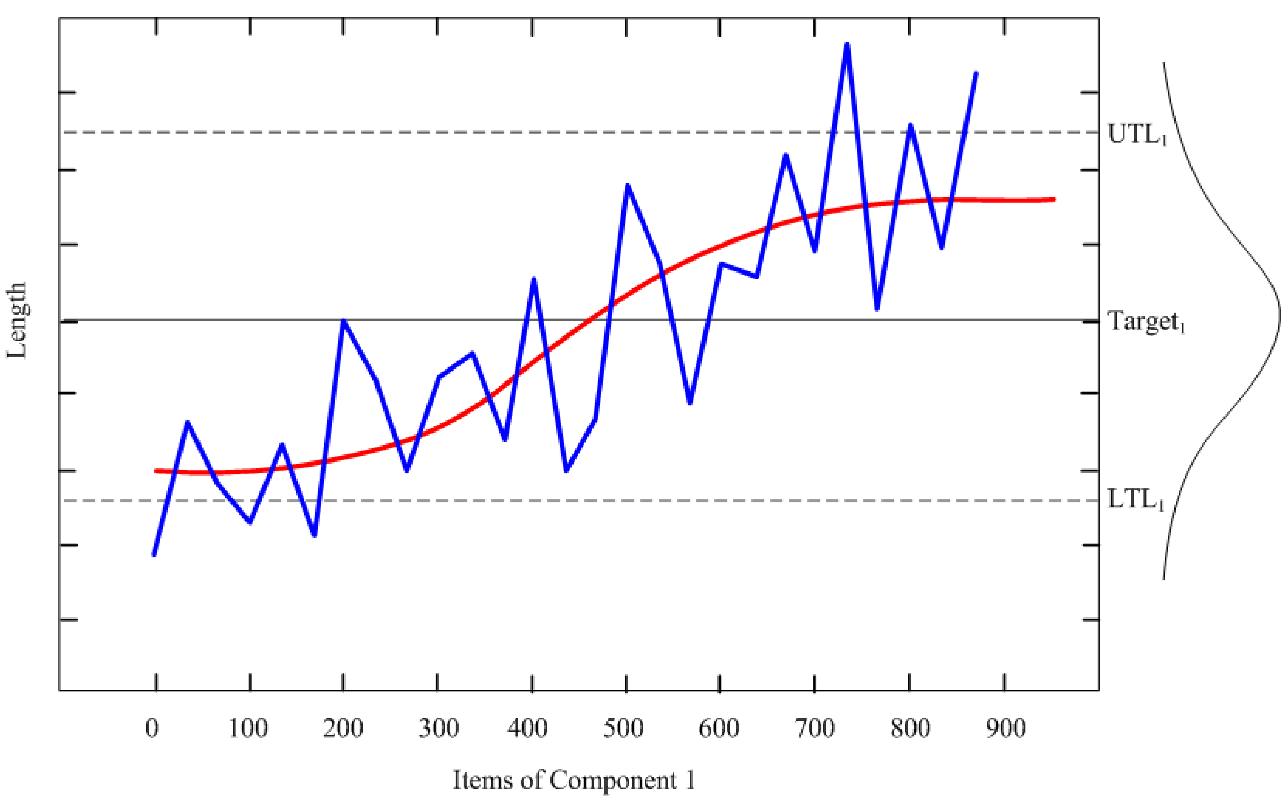


Figure 3-8. Superposition of random noise and a long-term drift.

A process whose variation can be described by a curve like the one in Figure 3-8 probably would have a low process capability index c_p and would give rise to a great number of defective units since many of them, presumably, fall out of the tolerance limits. Nonetheless, the mere presence of the long-term drift in the variation might offer a good opportunity to engineer a method to overcome this problem.

If a subset *i* of items of Component 1, produced consecutively in a short-term interval, were taken from the lot, the variation found there would probably be lower than the one of the whole lot [Bur79 ch.8 p.192]. Since the long-term drift needs time to develop itself, its influence on this subset would only be partial. Furthermore, most probably the items' length values found in this subset would not cover completely the nominal tolerance band $2t_1$. Instead, they would be most likely spread over a narrower band centered at $\mu_{1,sub(i)}$ (Figure 3-9).

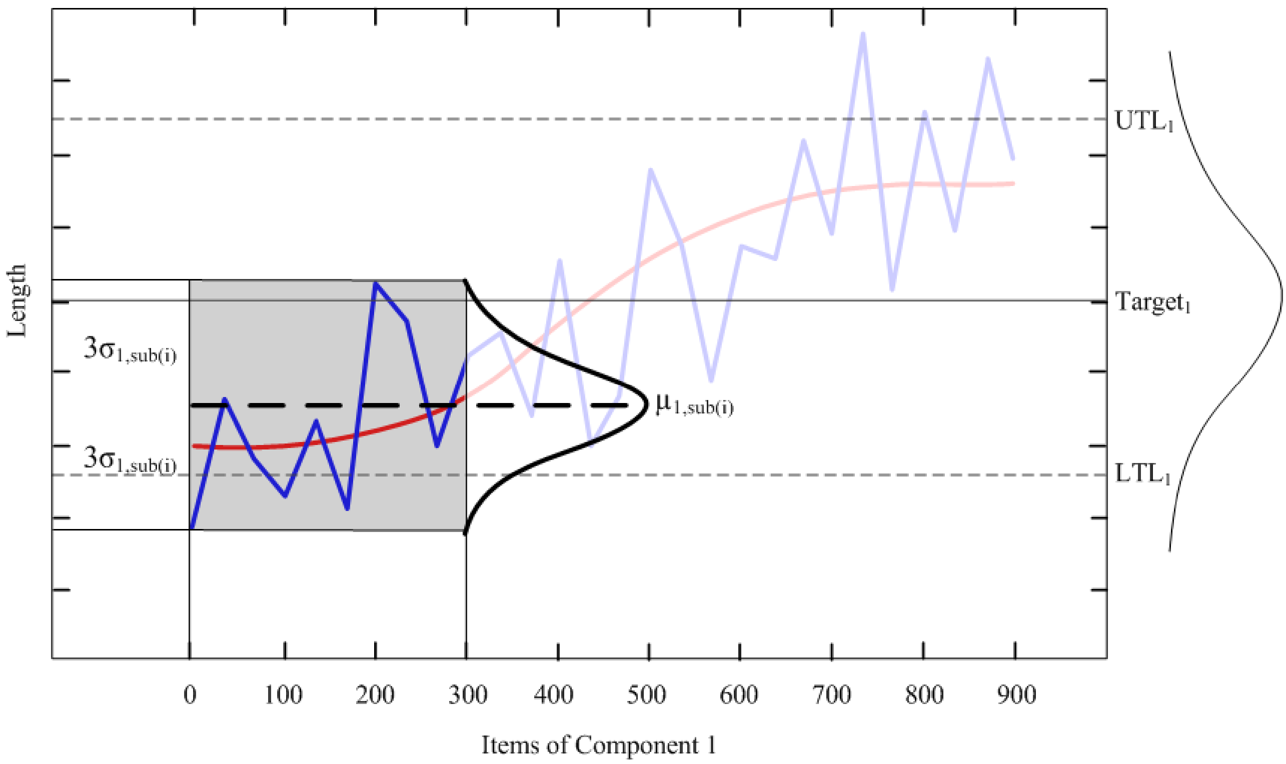


Figure 3-9. Variation found in the subset *i* of items of Component 1.

3.2.2. Tolerance Allocation and Target Adjustment

It is reasonable to think that, at least for the subset *i* in Figure 3-9, the nominal tolerance t_1 was not fully used and that part of it could have been spared to complement the nominal tolerance t_2 of a matching subset *i* of items of Component 2. In fact, it would have been enough to have a tolerance $t_{1,sub(i)}$ equal to three times the standard deviation $\sigma_{1,sub(i)}$ of the subset *i* to guarantee that 99.73% of the items were covered. With this, it would have been possible to define a adjusted tolerance $t_{2,adj,sub(i)}$. According to equation (3-38), if $\sigma_{1,sub(i)}$ were lower than σ_1, then the adjusted tolerance $t_{2,adj,sub(i)}$ could be made larger than the nominal tolerance t_2.

$$t_{1,sub(i)} = 3\sigma_{1,sub(i)} \tag{3-38}$$

$$t_{2,adj,sub(i)} = \sqrt{t_{assy}^2 - t_{1,sub(i)}^2} \tag{3-39}$$

If the mean $\mu_{1,sub(i)}$ of the items' length of Component 1 in the subset *i* were *a priori* known, it would be possible to define an adjusted target $L_{2,adj,sub(i)}$ for a matching subset *i* of items of Component 2 that forces the meeting of the desired nominal target L_{assy}.

$$L_{2,adj,sub(i)} = L_{assy} - \mu_{1,sub(i)} \tag{3-40}$$

In the discussion above, knowing $\mu_{1,sub(i)}$ and $\sigma_{1,sub(i)}$ would be sufficient to determine proper adjusted values for $L_{2,adj,,sub(i)}$ and $t_{2,adj,sub(i)}$ (Figure 3-10). Similar approach could be applied to a subsequent subset *(i+1)* of items of Component 1 to determine the adjusted target $L_{2,adj,sub(i+1)}$ and the tolerance $t_{2,adj,sub(i+1)}$ of a matching subset *(i+1)* of items of Component 2. The repeated application of these steps over a process that presents a detectable long-term drift (along with random noise) might lead to a significant reduction of the variation of the resulting assemblies' length and to the reduction of the mean shift. It is worthy to mention again that any tolerance enlargement will also generate an improvement in the potential capability index c_p (equation 3-24).

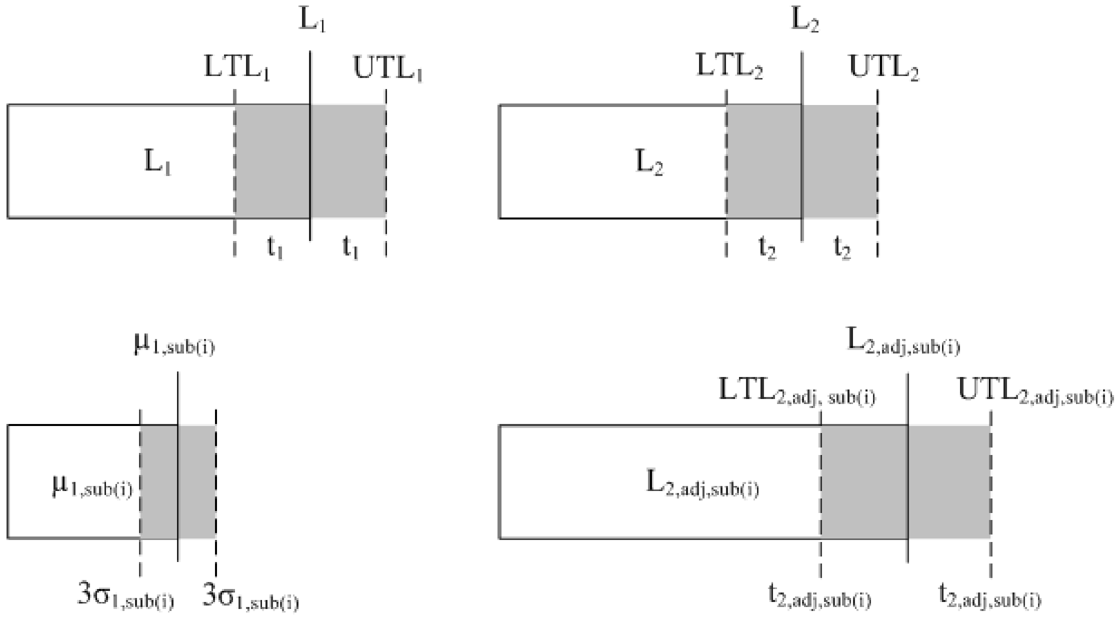


Figure 3-10. Adjusted target and tolerance for the items of subset *i* of Component 2.

In summary, SDSM can be regarded as a powerful statistical tool to help determine the right specification adjustments by means of sampling items produced consecutively in a short-time interval. However, an additional inspection effort is required to determine the estimates of $\mu_{1,sub(i)}$ and $\sigma_{1,sub(i)}$.

3.3. Statistical Feed-Forward Control Model (SFFCM)

SFFCM is the control model derived from the iterative application of SDSM and it can be considered the central matter of this thesis. SFFCM requires the separation of the process or system under study into a feeding and a controlled subsystem. These subsystems have to be identified and defined in such a way that an additional measurement step can be introduced between them to retrieve data about the actual values of the characteristics of interest (Figure 3-11). Thus, with the help of SDSM the data retrieved from the output of the feeding Subsystem A are used to adjust the parameters of the controlled Subsystem B so that the system output can be controlled from inside to prevent the occurrence of defective units.

The implementation of SFFCM only makes sense if a long-term drift in the variation of the characteristics of interest can be detected in the output of the feeding Subsystem A.

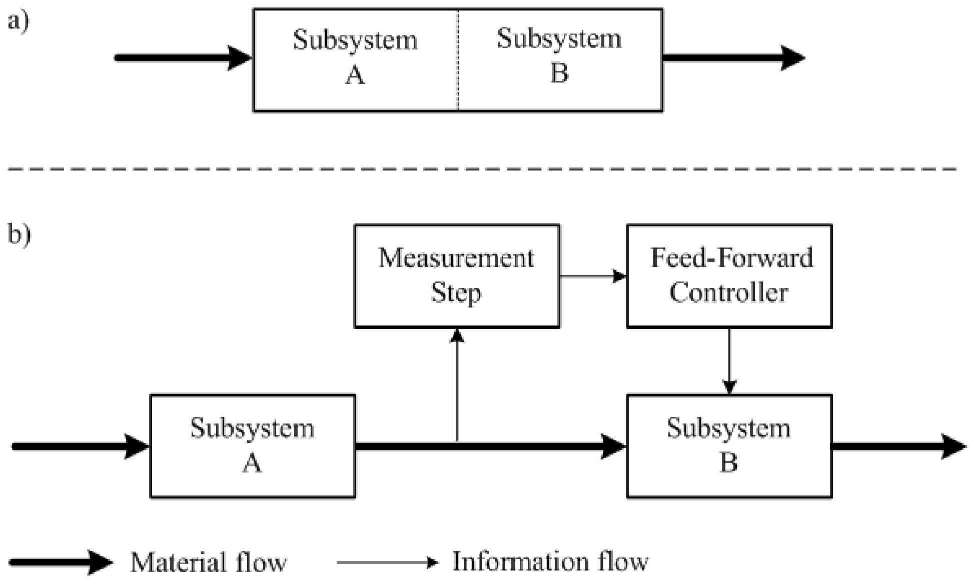


Figure 3-11. Feeding Subsystem A and controlled Subsystem B of SFFCM.

The application of SFFCM does not imply measuring 100% of the output of Subsystem A. Although an appropriate number of observations is needed. From this point of view, somehow SFFCM resembles the ideas behind the Statistical Process Control (SPC) [Ost75 ch.15 p.493, Pfe02 ch.5 p.165]. In contrast to classical approaches, however, a feed-forward loop is used instead of a feedback loop.

3.3.1. Subset Size

The subset size defines the number of consecutive items coming out of the feeding Subsystem A that are considered at once to draw the sample that will be used to determine the adjustments to the parameters of the controlled Subsystem B [Her11-1, Tut11].

3.3.2. Sampling Strategy and Sample Size

Since the success of SFFCM depends mostly on the ability to counter the influence of the long-term drift, it is crucial to make enough and representative observations of the items' length to describe properly its evolution over time. For the purposes of this work, the sampling strategy will comprise two aspects. The first one is the number of observations per subset, which is defined by the sample size. The second aspect is the way in which the items will be selected, either by means of simple or systematic random sampling [Ost75 ch.3 p.52].

3.3.3. Iterative Control

Assuming that the manufacturing processes of Component 1 and Component 2 represent the feeding Subsystem A and the controlled Subsystem B respectively, the effect of SFFCM will be reflected in the way in which the feed-forward controller forces the subsets of Component 2 respond to the drift detected in the items' length of the subsets of Component 1 (Figure 3-12 and Figure 3-13) [Her11-2].

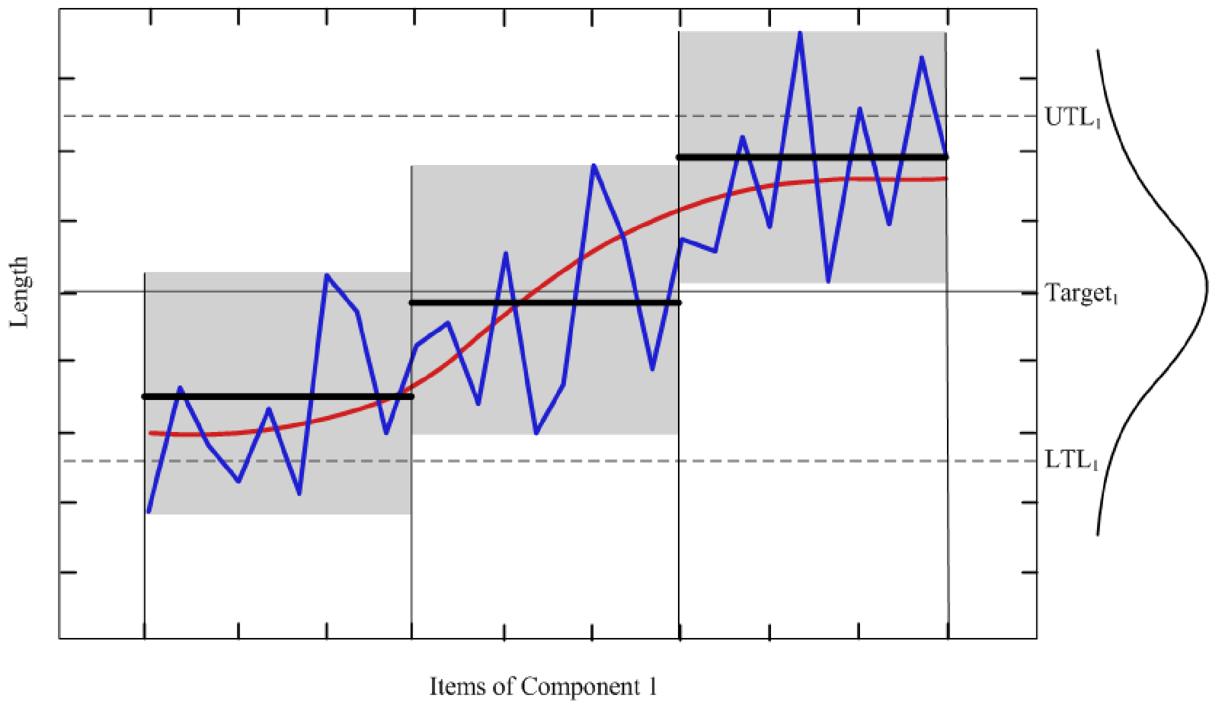


Figure 3-12. Subsets of Component 1.

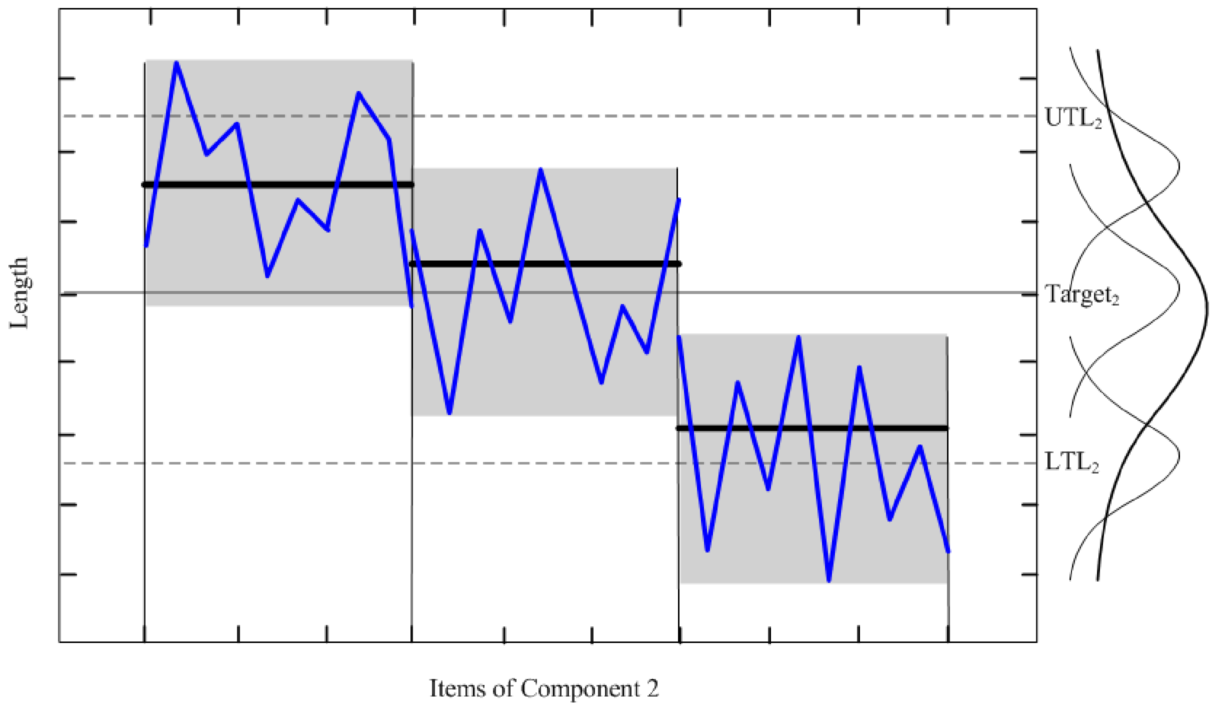


Figure 3-13. Subsets of Component 2 after the specification adjustments.

Since these two populations are correlated now, equation (3-9) has to include the corresponding correlation coefficient ρ as follows:

$$X_1 + X_2 \sim N\left(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2 + 2\rho\sigma_1\sigma_2\right) \tag{3-41}$$

3.4. Estimators of $\mu_{1,sub(i)}$ and $\sigma_{1,sub(i)}$

Determining proper estimates of the mean $\mu_{1,sub(i)}$ and the standard deviation $\sigma_{1,sub(i)}$ of the subset *i* from the data obtained after making a limited number of observations is not a trivial task. In fact, there is not a simple way to guarantee that the measurements obtained from a bunch of items will cover completely the spectrum of actual values existing in a given subset. Thus, there is no reason to expect that the sample mean $\bar{x}_{1,sub(i)}$ and the sample standard deviation $s_{1,sub(i)}$ will be identical to the subsets' parameters $\mu_{1,sub(i)}$ and $\sigma_{1,sub(i)}$ (Figure 3-14).

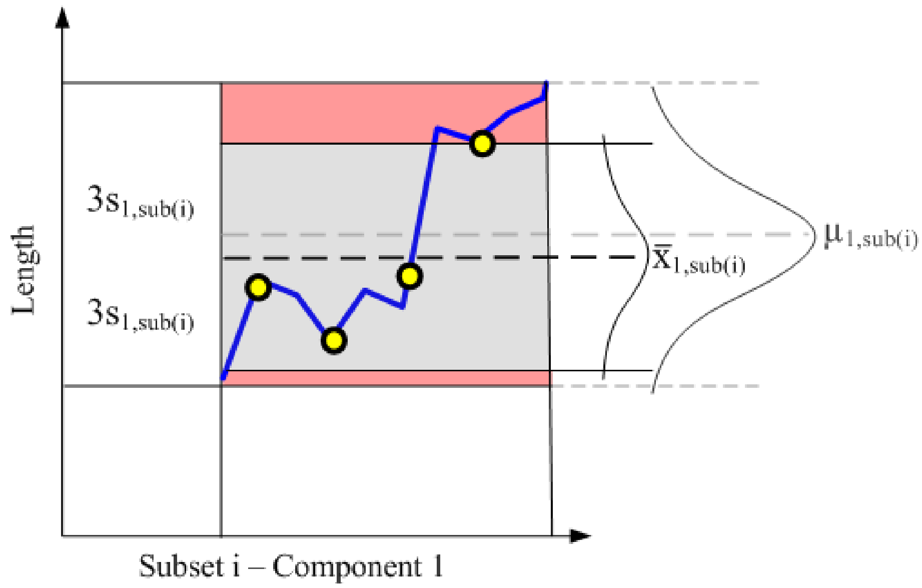


Figure 3-14. Sample mean $\bar{x}_{1,sub(i)}$ and sample standard deviation $s_{1,sub(i)}$ of subset *i*.

Since SDSM relies on that 99.97% of the items of the subset *i* fall in the band $\mu_{1,sub(i)} \pm 3\sigma_{1,sub(i)}$, the use of $\bar{x}_{1,sub(i)}$ and $s_{1,sub(i)}$ as estimators of $\mu_{1,sub(i)}$ and $\sigma_{1,sub(i)}$ could leave some of the items out of any consideration. Specially, if the sampled items used to compute $\bar{x}_{1,sub(i)}$ and $s_{1,sub(i)}$ are not really representative of the subset *i* [Her12-1]. Keeping this in mind, proper estimators of $t_{1,sub(i)}$ and $t_{2,adj,sub(i)}$ (equations 3-38 and 3-39) can be defined as follows:

$$\hat{t}_{1,sub(i)} = 3s_{1,sub(i)} \tag{3-42}$$

$$\hat{t}_{2,adj,sub(i)} = \sqrt{t_{assy}^2 - \hat{t}_{1,sub(i)}^2} \tag{3-43}$$

An extended tolerance $t_{2,adj,sub(i)}$ might produce an eventual reduction of the number of items falling out of the tolerance zone and an improvement of the capability indices c_p and c_{pk}. Thus, the corresponding equations 3-24 and 3-25 can be rewritten as follows:

$$c_{p,adj,sub(i)} = \frac{t_{2,adj,sub(i)}}{3\sigma_2} \tag{3-44}$$

$$c_{pk,adj,sub(i)} = \min\left\{ \frac{\left(L_{2,adj,sub(i)} + t_{2,adj,sub(i)}\right) - \mu_{2,adj,sub(i)}}{3\sigma_2}, \frac{\mu_{2,adj,sub(i)} - \left(L_{2,adj,sub(i)} - t_{2,adj,sub(i)}\right)}{3\sigma_2} \right\} \tag{3-45}$$

3.4.1. Central Tendency Measure

It has been already explained that SFFCM exerts the control by means of determining the appropriate adjusted values of $L_{2,adj,sub(i)}$ that counter the drift experienced by $\mu_{1,sub(i)}$ over time. Therefore, finding the correct value of the central tendency measure for each subset i is crucial to succeed. The corresponding estimator can be defined as follows:

$$\hat{L}_{2,adj,sub(i)} = L_{assy} - \bar{x}_{1,sub(i)} \tag{3-46}$$

Even though $\bar{x}_{1,sub(i)}$ is the best estimator of $\mu_{1,sub(i)}$, it considers only the most recently inspected sample, i.e., it is computed using only the measurement made on the last inspected subset i. However, $\bar{x}_{1,sub(i)}$ does not consider the measurements made on previous subsets k (with $k=1,2...i-1$). In other words, $\bar{x}_{1,sub(i)}$ lacks of “memory”.

It has been also said that the success of SFFCM depends greatly on the ability to counter the long-term drift, which requires the observation of its evolution over a lapse of time longer than the interval occupied by a single subset. Therefore, it is necessary to find the way to model the drift so that the best adjustments can be determined. For this purpose, the sample mean $\bar{x}_{1,sub(i)}$ may not be the most promising choice.

Commonly, adaptive assembling techniques rely on the sample mean $\bar{x}_{1,sub(i)}$ to compute the necessary adjustments for the process parameters. In this work, however, along with $\bar{x}_{1,sub(i)}$ a new estimator “with memory” is proposed and studied: the cumulative de-noised average $\bar{x}_{1,cdna,sub(i)}$.

3.4.1.1. Cumulative De-Noised Average (CDNA)

The computation of the cumulative de-noised average $\bar{x}_{1,cdna,sub(i)}$ guarantees that the data gathered over a period of time is being taken into account. Basically, the measurements of the current and some of the previous subsets are processed by a wavelet-based de-noising algorithm that delivers a new set of points that are used then to construct a statistical model, usually a polynomial of 2nd degree, to describe it. This model is then used to fit a smoother curve from which the proposed estimator $\bar{x}_{1,cdna,sub(i)}$ is determined by means of averaging the points corresponding to the subset *i*. The procedure is repeated every time that a new set of measurements is made. (Figure 3-15). Further details are given in Appendix A.

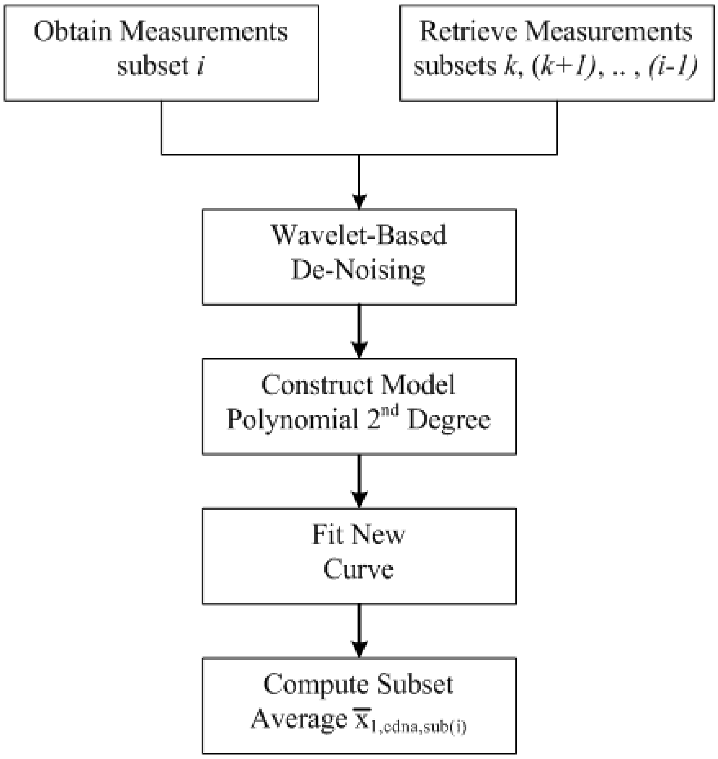


Figure 3-15. Computation of the cumulative de-noised average $\bar{x}_{1,cdna,sub(i)}$.

In this case, the estimator of $\hat{L}_{2,adj,sub(i)}$ is defined as follows:

$$\hat{L}_{2,adj,sub(i)} = L_{assy} - \bar{x}_{1,cdna,sub(i)} \tag{3-47}$$

The idea behind the cumulative de-noised average and the steps to compute it can be better understood graphically with the help of Figure 3-16, Figure 3-17 and Figure 3-18.

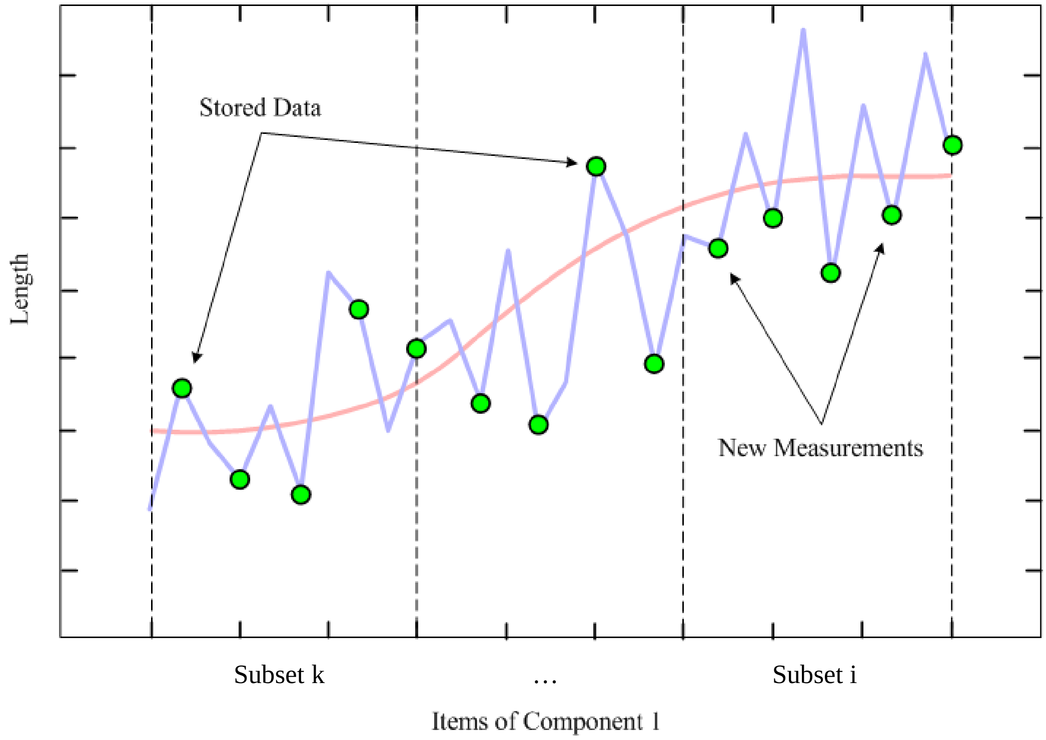


Figure 3-16. Computation of $\bar{x}_{1,cdna,sub(i)}$ - Gather available measurements.

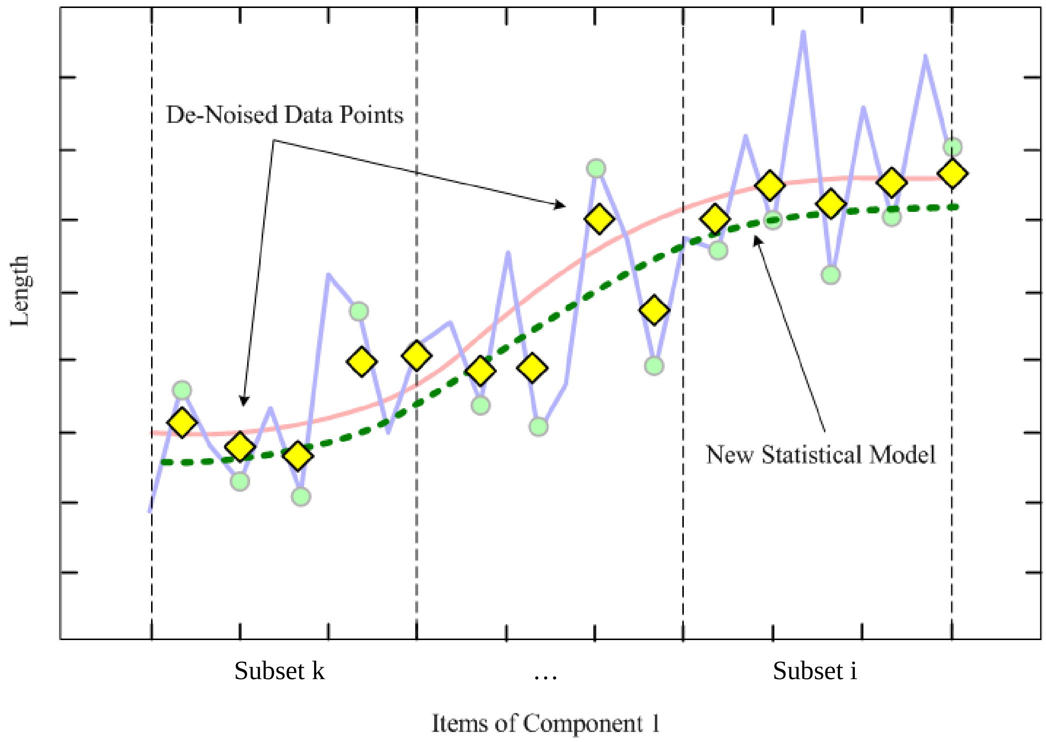


Figure 3-17. Computation of $\bar{x}_{1,cdna,sub(i)}$ - Reduce noise and construct a statistical model.

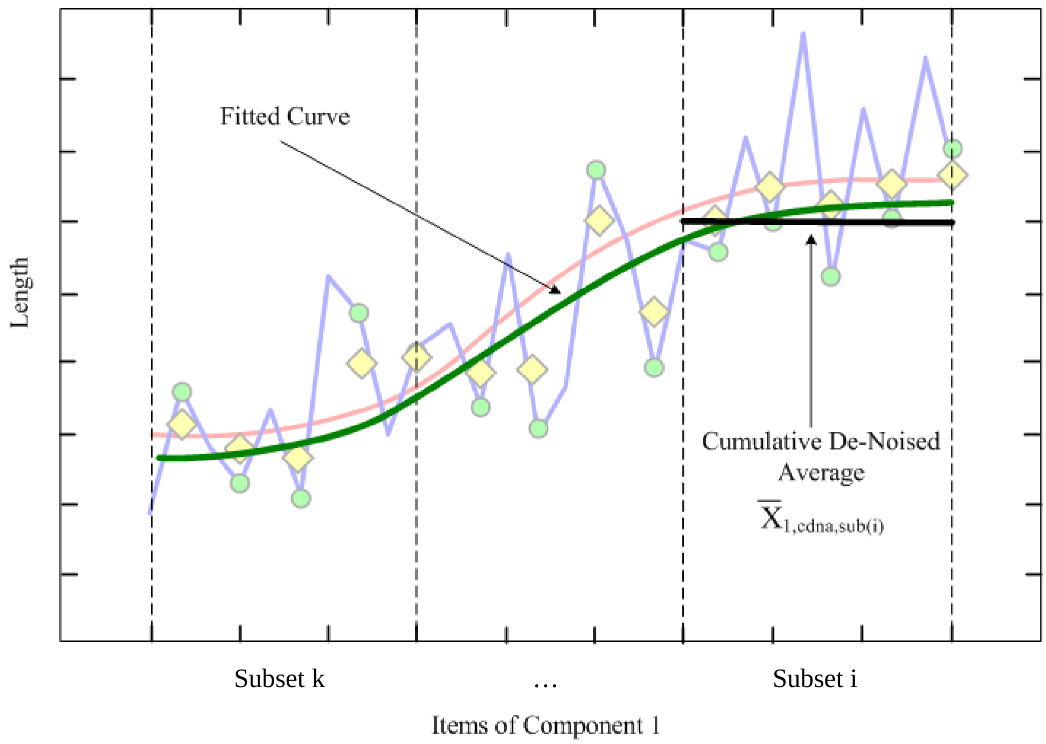


Figure 3-18. Computation of $\bar{x}_{1,cdna,sub(i)}$ - Fit the curve and average points of subset *i*.

An alternative to the arithmetic average used to compute CDNA is the integral average, in which the area under the fitted curve is considered instead. The following are the corresponding equations:

$$\bar{x}_{1,cdna,\text{int},sub(i)} = \frac{1}{\Delta x}\int_{i-1}^{i} f_{fit}(x)dx \tag{3-48}$$

$$\hat{L}_{2,adj,sub(i)} = L_{assy} - \bar{x}_{1,cdna,\text{int},sub(i)} \tag{3-49}$$

3.5. Uncertainty of the Measurements

The result of a measurement is only an approximation or estimate of the true value of the measurand and thus, it needs to be accompanied by a statement of the uncertainty of that estimate.

The uncertainty is a parameter associated with the result of a measurement that characterizes the dispersion of the values that could reasonably be attributed to the measurand. The parameter may be, for example, a standard deviation or the half-width of an interval having a stated level of confidence. Uncertainty of measurement comprises many components. Some of them may be evaluated from the statistical distribution of the results of series of measurements and can be characterized by experimental standard deviations. Other components, instead, may be evaluated from assumed probability distributions based on experience or other information. It is understood that the result of the measurement is the best estimate of the value of the measurand, and that all components of uncertainty, including those arising from systematic effects, such as components associated with corrections and reference standards, contribute to the dispersion [JCGM_100_2008 p.36].

3.5.1. Accuracy of Measurement and Precision

The accuracy is the closeness of the agreement between the result of a measurement and a true value of the measurand. Accuracy is a qualitative concept that differs from the term precision [JCGM_100_2008 p.35].

The precision of a measurement system is the degree to which repeated measurements under unchanged conditions spread out around the average value [Mor10 ch.9 p.103].

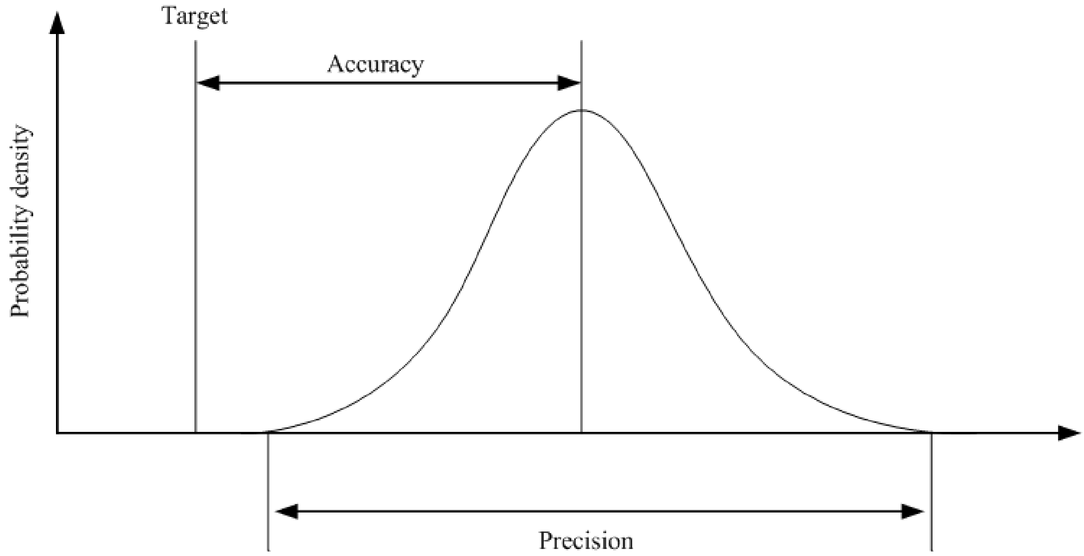


Figure 3-19. Accuracy and precision.

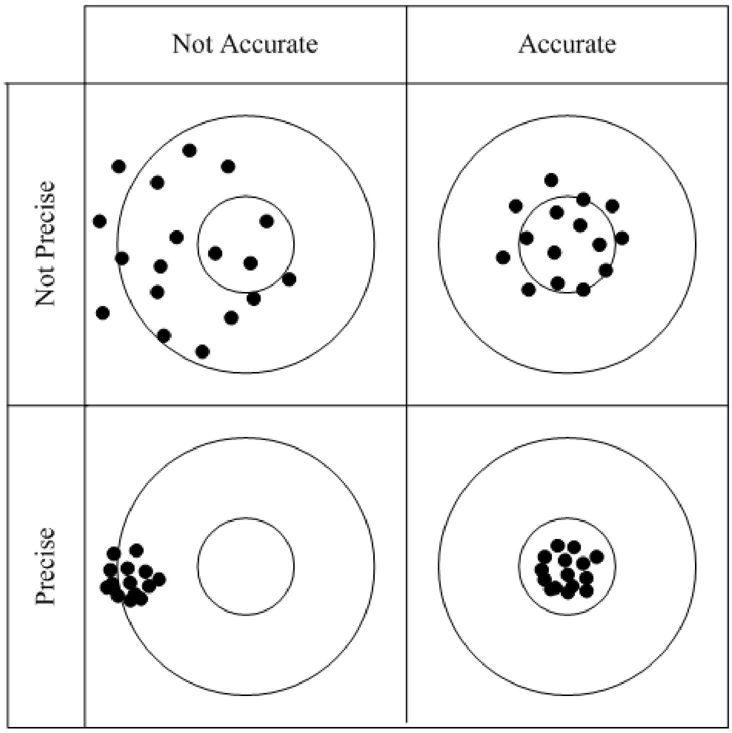


Figure 3-20. Difference between accuracy and precision [Mor10 ch.9 p.103].

In the context of SFFCM, once the sample mean $\bar{x}_{1,sub(i)}$ and the sample standard deviation $s_{1,sub(i)}$ of the subset *i* of Component 1 have been determined, the estimator of the adjusted target of the matching subset *i* of Component 2 can be directly defined as follows:

$$\hat{L}_{2,adj,sub(i)} = L_{assy} - \bar{x}_{1,sub(i)} \tag{3-50}$$

However, when computing the corresponding tolerance of subset i of Component 2 the measurement uncertainty should be taken into account. For this reason, the "measured" tolerance $\hat{t}_{1,sub(i)}$ of a given subset i should not be assumed to be equal to $3s_{1,sub(i)}$ anymore (equation 3-41). Now, the valid formula includes the term that represents the measurement uncertainty.

$$\hat{t}_{1,sub(i),unc} = \hat{t}_{1,sub(i)} + u \tag{3-51}$$

If $\Delta t_{1,sub(i)}$ defines the difference between the nominal tolerance t_1 and half of the band of $6\,s_{1,sub(i)}$ where 99.73% of the items' length are believed to fall and u is the measurement uncertainty, the relation between $\Delta t_{1,sub(i)}$ and u can expressed by means of the ratio defined in the equation (3-53). This relations is represented graphically Figure 3-21.

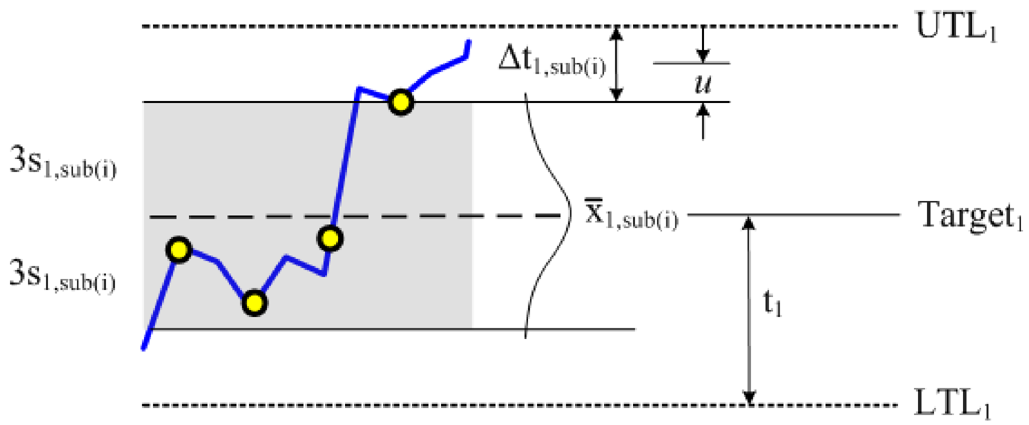


Figure 3-21. Representation of the measurement uncertainty.

$$\Delta t_{1,sub(i)} = t_1 - 3s_{1,sub(i)} \tag{3-52}$$

$$X\% = \frac{u}{\Delta t_{1,sub(i)}} \tag{3-53}$$

To avoid proceeding with an analysis in terms of a given value u of the measurement uncertainty, equation 3-51 can be rewritten in terms of the variable ratio $u/\Delta t_{1,sub(i)}$.

$$\hat{t}_{1,sub(i),unc} = \hat{t}_{1,sub(i)} + (X\%)\Delta t_{1,sub(i)} \tag{3-54}$$

$$\hat{t}_{1,sub(i),unc} = 3s_{1,sub(i)} + (X\%)(t_1 - 3s_{1,sub(i)}) \tag{3-55}$$

Thus, the adjusted tolerance of the matching subset *i* of Component 2 can be computed as follows:

$$\hat{t}_{2,adj,sub(i),unc} = \sqrt{t_{assy}^2 - \hat{t}_{1,sub(i),unc}^2} \tag{3-56}$$

3.6. Response Delay

The effectiveness of a controller depends greatly on the ability to respond promptly to any detectable deviation. Therefore, it is a matter of mayor interest to study how response delays affect the ability of the proposed SFFCM to counter the effect of the long-term drift.

In the context of the SFFCM, a response delay can be defined as the interval of time between the calculation of an adjustment and the response observed on the output of the controlled Subsystem B. If the production lines of Component 1 and Component 2 are part of a sequential scheme in which the corresponding conveyors are synchronized and running at the same speed, the presence of response delays will impede the perfect synchronicity of the items of the respective matching subsets *i* of each component. Thus, depending on the length of the delays, the first few items of the subset *i* of Component 2 will not be really affected by the adjustment determined by the measurements made on the subset *i* of Component 1 (Figure 3-22).

To get rid of the side parameters like the conveyors' speed, in this work, response delays are expressed in terms of the number items, or its relative percentage, of a given subset *i* of Component 2 that were transported during the delay and that, in consequence, were not adjusted. This percentage will remain constant if the response delay and the subset size are fixed. However, if a variable subset size strategy is implemented, the percentage will vary from subset to subset as well.

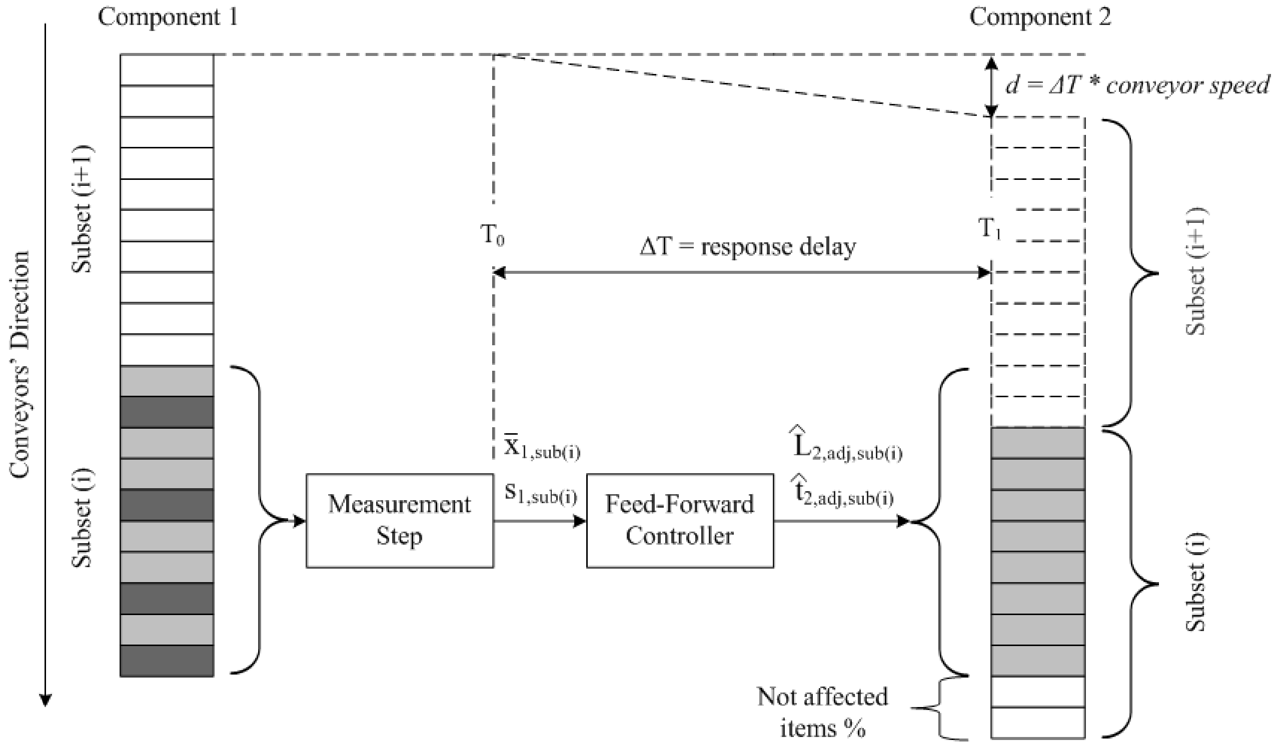


Figure 3-22. Response delay.

3.7. Assembling of Multiple Components

Most of the existing assembling techniques were conceived to deal with the problem of mating two components. It is not hard to realize the complexities that an additional component might bring along when, for instance, a selective assembling scheme is in place. The range of potential difficulties is quite extensive, from the allocation of additional resources to perform full inspections (100%), passing through the definition of the proper binning strategy [Ker03 ch.4 p.143] as well as the inventory management and up to the assembling task itself. It can be argued that a selective assembly could reduce the scrap level of the resulting assemblies; however, the costs related to the production and storage of those tolerance groups that perhaps can not be matched immediately should be also included in the analysis [Man61].

In practice, however, any multi-component assembling problem can be simplified and reduced to a two-component-assembling situation by means of assembling neighbor components to conform two preliminary subassemblies that can be then mated using a selection-based technique.

Given that SFFCM is not based on any selective scheme but on the separation of the system in two subsystems to collocate a measurement step between them, all the complications associated to an eventual multi-component assembling challenge are circumscribed to the definition of the subsystems. Either for two or more components, SFFCM's inner working remains the same. Nevertheless, the selection of the position for the measurement point should not be taken lightly because that decision might have a great impact on the controller effectiveness (Figure 3-23).

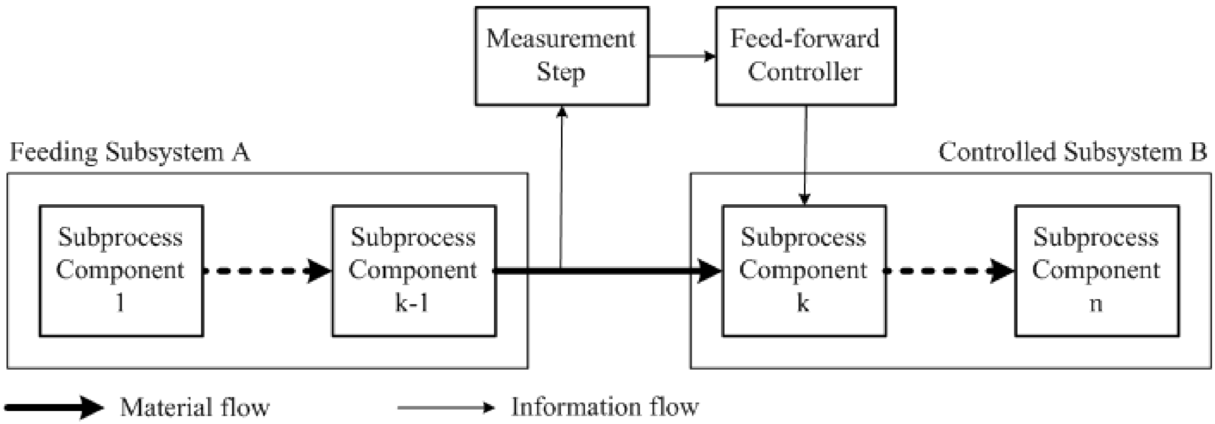


Figure 3-23. Multi-component assembling scheme.

3.8. Parallel Manufacturing

In parallel configurations where component items are produced simultaneously in different lines, alternative to overcome the offset problem should be studied. Since matching subsets are not produced one after another but at the same time, it would not be possible to correct immediately eventual deviations detected in the subset *i* of Component 1 by means of adjusting the target of the matching subset *i* of Component 2 because the latter has been already fabricated (Figure 3-24). In fact, the data obtained from the subset *i* of Component 1 could be not even useful such as it is for any posterior adjustment of the subsequent subset *(i+1)* of Component 2 because variation of the corresponding subset *(i+1)* of Component 1 could be substantially different.

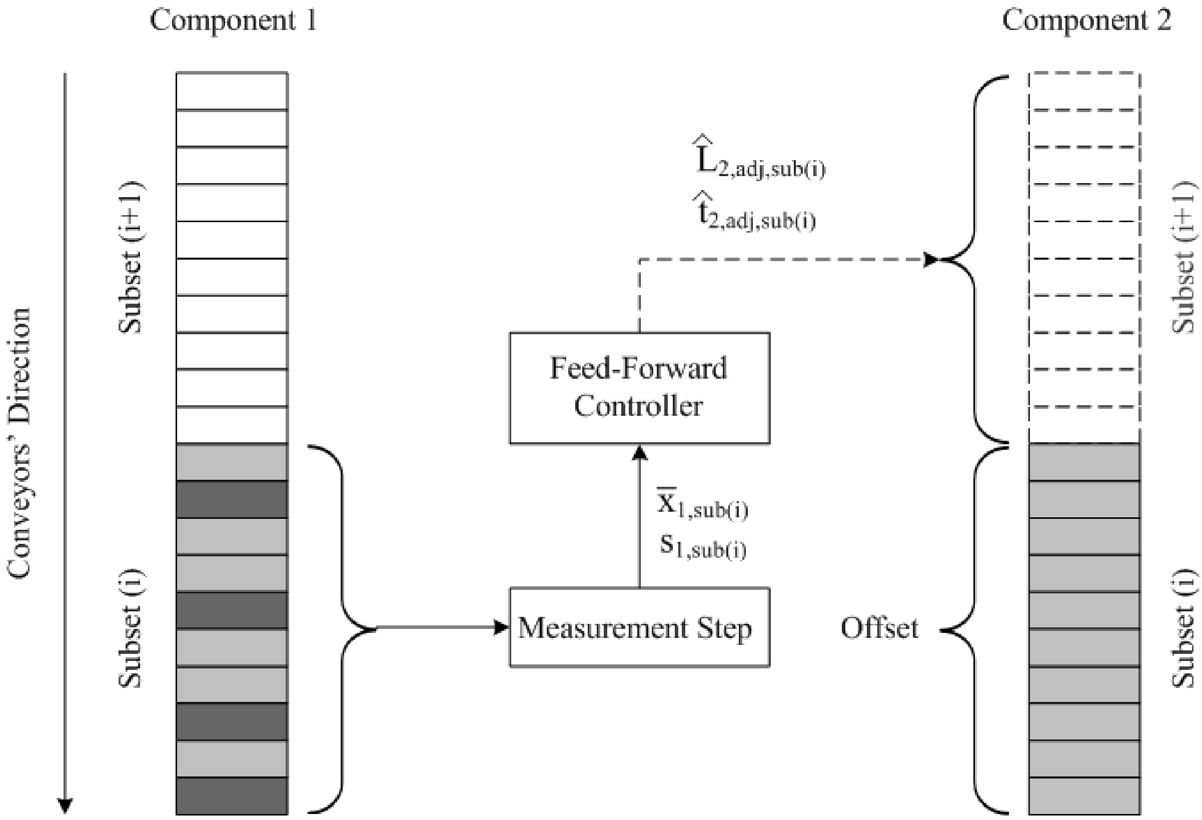


Figure 3-24 Offset in a parallel manufacturing configuration.

3.8.1. Prediction Modes

The approach proposed to overcome the offset problem considers the utilization of several statistic models to predict the sample mean of the subsequent subset *(i+1)* of Component 1 using the data retrieved from the measurements made on some of the previous subsets. The predicted statistics will be then used as the input to the feed-forward controller so that new estimators for the adjusted specifications of subset *(i+1)* of Component 2 can be defined (Figure 3-25).

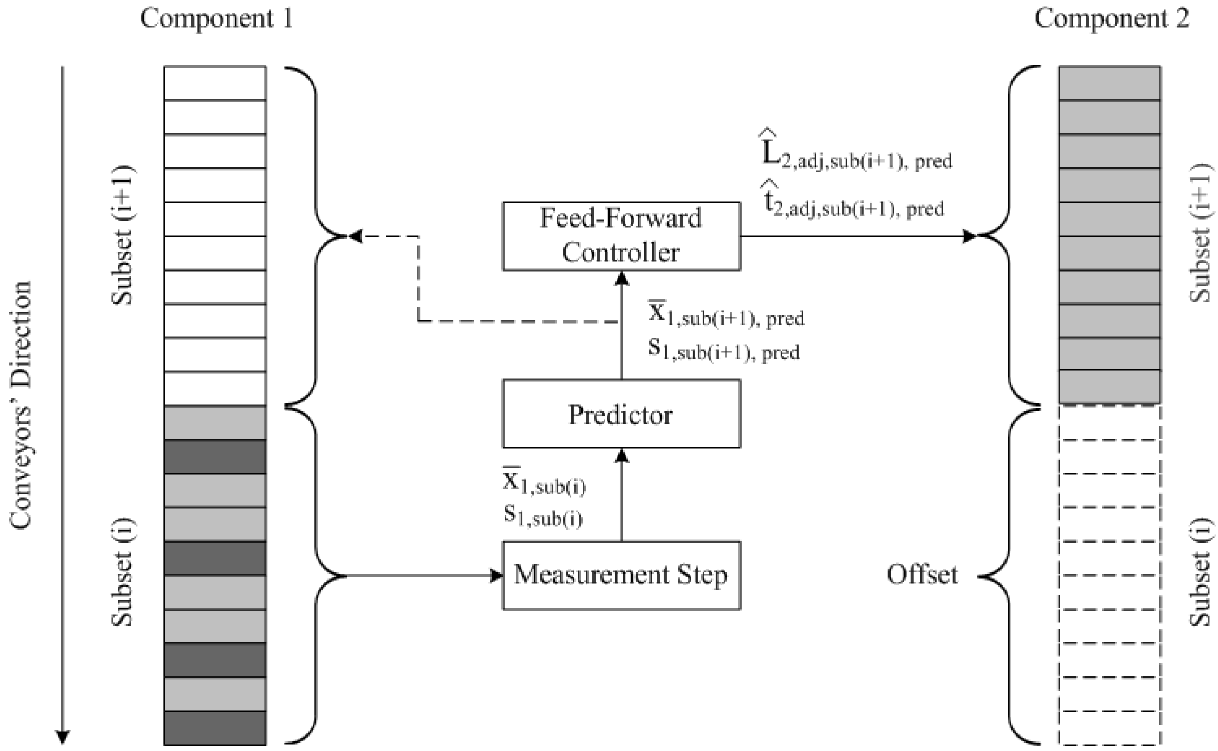


Figure 3-25. Prediction module in a parallel manufacturing scheme.

According to SFFCM, the prediction is repeated subset after subset until the all the items are assembled. In particular, since the nominal specifications of the subset 1 of Component 2 will remain unaltered through out the process, the items inside will have to be assembled such as they are.

Although the standard deviation may evolve over time, in this work the prediction of the sample standard deviation of the subset *(i+1)* of Component 1 is left identical to the measured $s_{1,sub(i)}$.

$$s_{1,sub(i+1),pred} = s_{1,sub(i)} \tag{3-57}$$

In the case of the sample mean, three different prediction approaches have been defined. The first prediction mode, and the most conservative, uses the same sample mean obtained from the subset *i* as the prediction for the subset *(i+1)*. The second approach employs a robust regression algorithm that considers the data retrieved from some of the previous subsets to construct a statistical model with a polynomial of first degree. Among other benefits, this algorithm offers special robustness to outliers (Figure 3.26).

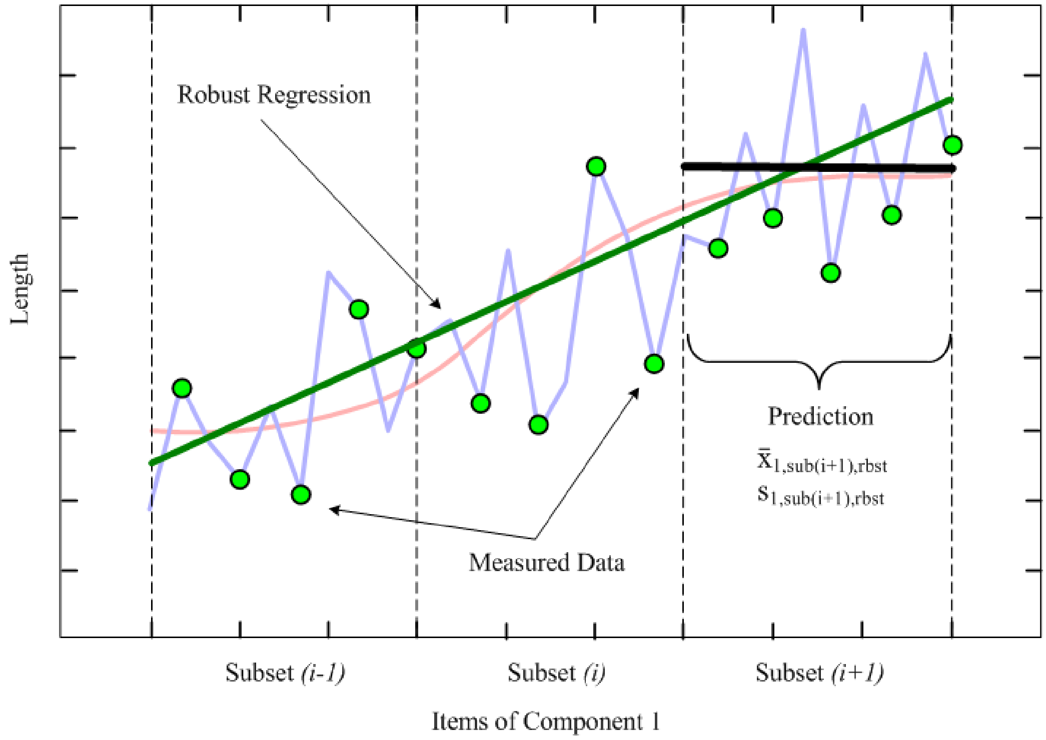


Figure 3-26. Prediction mode based on a robust regression algorithm

The third prediction mode requires the construction of polynomials of second order whose coefficients are calculated using data previously processed by a wavelet-based de-noising algorithm and then fitted in a least square sense (Figure 3-27).

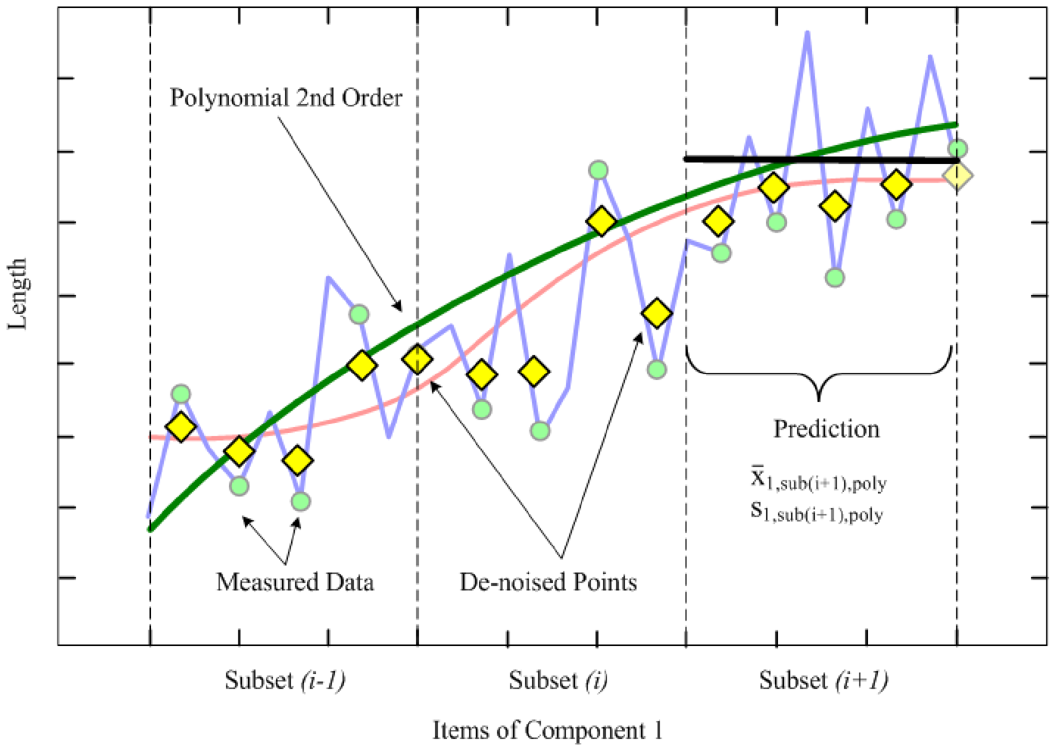


Figure 3-27. Prediction mode based on the construction of polynomials of 2nd order.

Either in the case of the robust regression or in the case of the polynomials of 2nd order, the predicted sample mean of the subset *(i+1)* is finally calculated by means of averaging the corresponding points of the fitted curve. The estimators to compute the specification adjustments of the subset *(i+1)* of Component 2 can be defined as follows:

$$\hat{L}_{2,adj,sub(i+1),pred} = L_{assy} - \bar{x}_{1,sub(i+1),pred} \tag{3-58}$$

$$\hat{t}_{2,adj,sub(i+1),pred} = \sqrt{t_{assy}^2 - \hat{t}_{1,sub(i+1),pred}^2} \tag{3-59}$$

where $\hat{t}_{1,sub(i+1),pred}$ can be computed directly (see equation 3-57).

$$\hat{t}_{1,sub(i+1),pred} = 3s_{1,sub(i+1),pred} \tag{3-60}$$

Further details about de wavelet-based de-noising algorithm and the curve fitting alternative can be found in Appendix A.

3.9. Complementary External Feedback Loop

The fundamental principle behind SFFCM is the correction of any detectable deviation from within the system so that the occurrence of defective items can be effectively prevented. Nevertheless, the proposed model lends itself to be complemented with a feedback loop whose own measurement sensor can be installed at the end of the assembling line to monitor the output of the controlled Subsystem B. In this configuration, the feedback controller feed the input to the controlled Subsystem B just like the feed-forward controller does (Figure 3-28).

Logically, besides all the technical complexities associated to the implementation of a complementary inspection module, additional resources would have to be allocated permanently for the measurement activities. Since inspection might be costly and time consuming, it has to be optimized whenever it is possible.

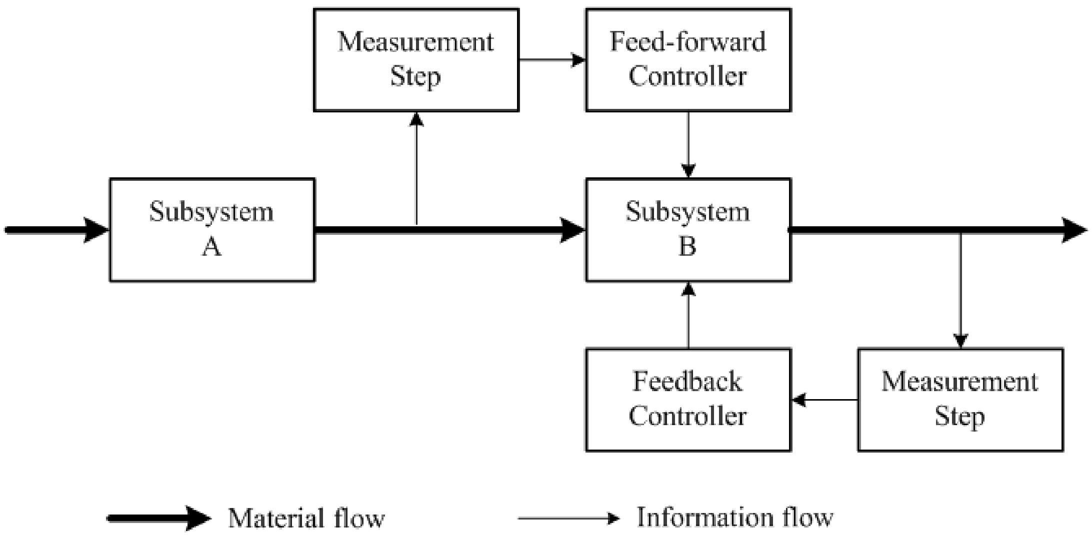


Figure 3-28. Feed-forward and complementary external feedback loop.

In this new configuration, with the help of the external feedback controller a small group of finished assemblies per subset can be randomly sampled and inspected. With this, the specifications of the subsequent subset of items of Component 2 can be adjusted not only using the data provided by the feed-forward controller but also taking into account the mean shift found by the feedback controller between the assembly nominal target L_{assy} and the sample mean of the inspected assemblies $\bar{x}_{assy,adj,sub(i)}$ (*hint: the use of the subscript "adj" indicates that the assembly items were produced under the action of SFFCM*).

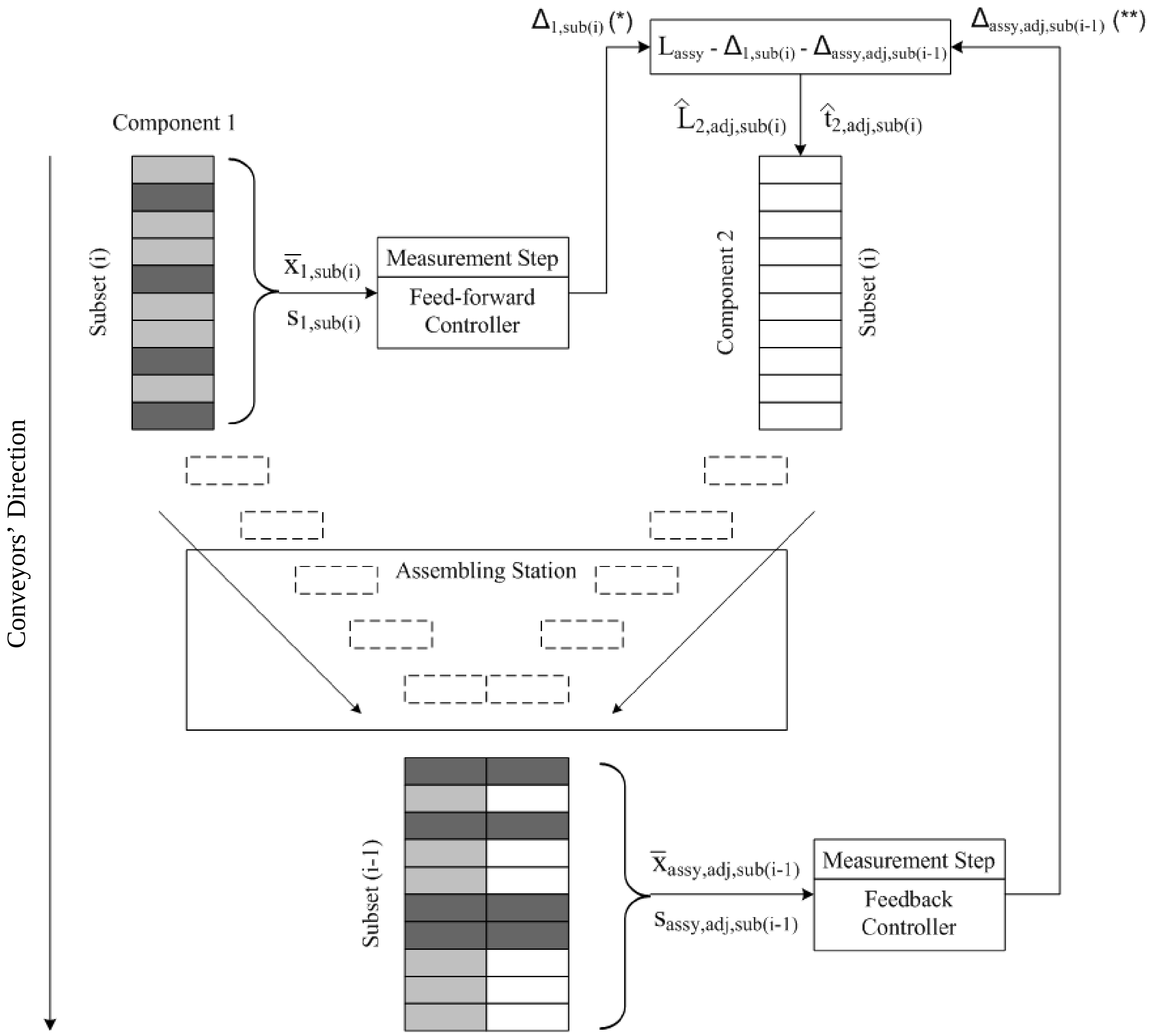
For a given subset *i* of Component 1, the difference between the nominal target L_1 and the sample mean $\bar{x}_{1,sub(i)}$ can be determined using the sensor of the feed-forward loop. Whereas, for the previous subsets *(i-1)* of the Component 1 and Component 2 that were assembled right before, the difference between the assembly nominal target L_{assy} and the sample mean $\bar{x}_{assy,adj,sub(i-1)}$ can be determined using the sensor of the feedback loop. Thus, the adjusted target of the subset *i* of Component 2 can be defined taking into consideration all the available information.

$$\Delta_{1,sub(i)} = \bar{x}_{1,sub(i)} - L_1 \tag{3-61}$$

$$\Delta_{assy,adj,sub(i-1)} = \bar{x}_{assy,adj,sub(i-1)} - L_{assy} \tag{3-62}$$

$$\hat{L}_{2,adj,sub(i)} = L_2 - \Delta_{1,adj,sub(i)} - \Delta_{assy,adj,sub(i-1)} \tag{3-63}$$

In Figure 3-29 it is shown how the interaction of the feed-forward and feedback loops occurs. Even though evident, the practical effect of this interaction is not trivial at all. While the feed-forward loop uses the present context to influence future states, the feedback loop uses past states to influence the present context. In Figure 3-29, subsets *i* represent the present, whereas subsets *(i-1)* belong with the past. Under this scheme, the first assembled subsets (i=1) will be never fed back.



(*) $\Delta_{1,sub(i)} = \bar{x}_{1,sub(i)} - L_1$

(**) $\Delta_{assy,adj,sub(i-1)} = (\bar{x}_{assy,adj,sub(i-1)} - L_{assy})$

Figure 3-29. Configuration of SFFCM with a complementary external feedback controller.

3.10. Complementary Internal Feedback Loop

Since SFFCM focuses the efforts on adjusting the parameters of the Subsystem B to counter the variation detected in the output of the Subsystem A, the proposed model lacks of a monitoring mechanism to control the output of Subsystem A. This fact might become a problem if the influence of the drift makes the variation go beyond the warning or the tolerance limits.

To overcome this potential problem the implementation of an internal feedback controlled is proposed (Figure 3-30). The expected effect on the variation is shown in Figure 3-31.

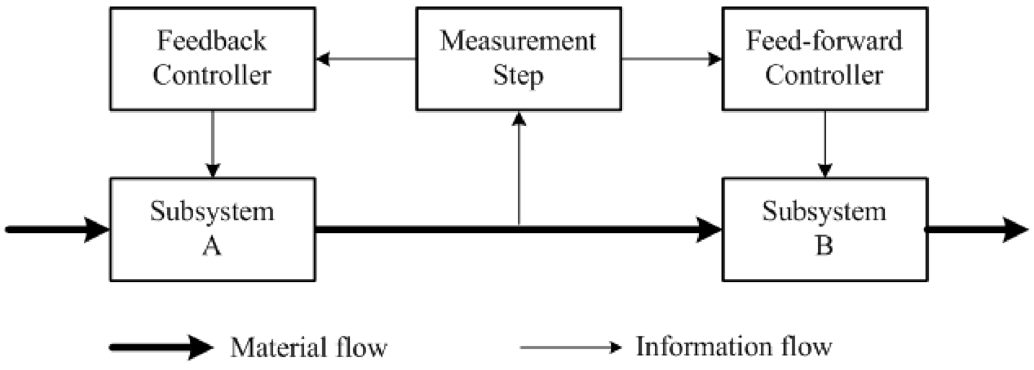


Figure 3-30. Complementary internal feedback loop.

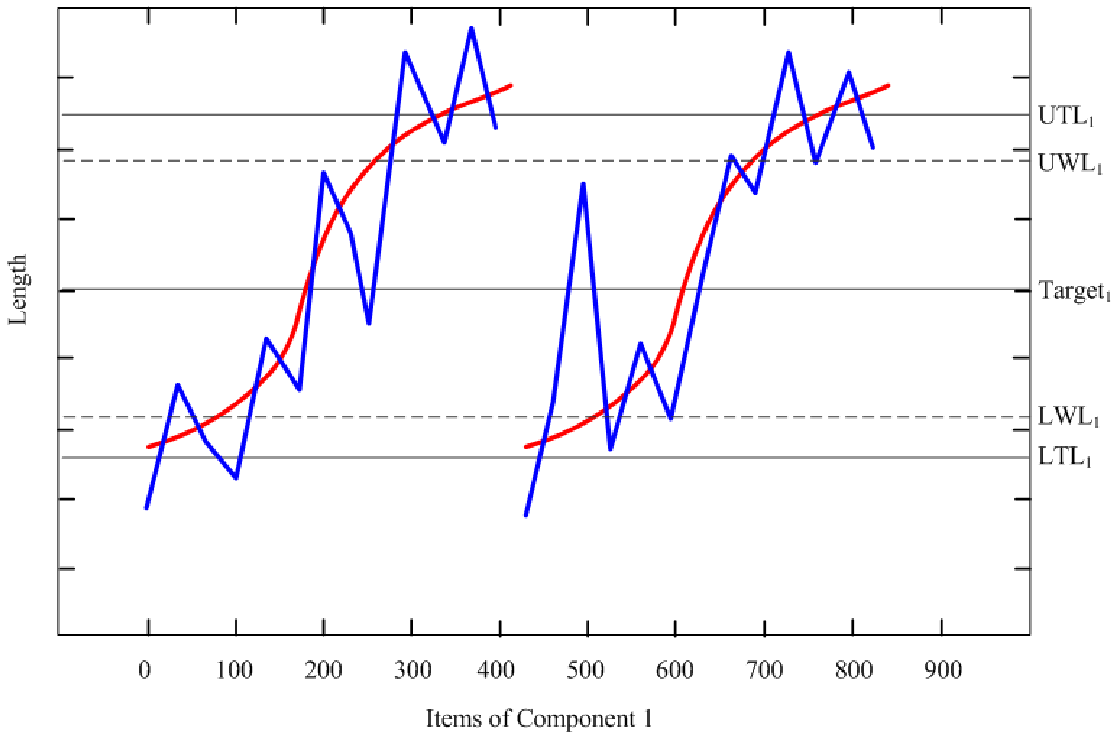


Figure 3-31. Effect of the internal feedback loop.

3.11. Chapter Summary

In this chapter, theoretical aspects and considerations of the proposed SFFCM were presented. In the first introductory sections, a brief review of the theory behind the tolerance stacking methods, the normal distributions and the statistical process control was presented.

The Statistical Dynamic Specifications Method (SDSM) was presented as the cornerstone of the Statistical Feed-Forward Control Model (SFFCM). SDSM takes advantage of the properties of normal distributions to apply statistics over subsets of the items to help determine adjustments to the specifications, target and tolerance, of the components of an assembly.

The central part of the chapter is dedicated to the proposed SFFCM, its advantages and limitations, and the conditions under which it can be applied. The implementation of SFFCM implies the separation of the system under study in two subsystems, a feeding and a controlled one, to collocate a measurement step between them.

There are four conditions that the system should fulfill to apply SFFCM: the characteristic of interest of the components has to be normally distributed and statistically independent, there should not be correlation between the component lots, the dimensional variation has to posses a detectable long-term component (the so-called drift) and the controlled subsystem has to be stable to admit adjustments without going out of control.

SFFCM is rather complex and there is a number of factors that might impact deeply the performance of the proposed controller. Some of the most important ones are the subset size, the inspection rate or sample size, the sampling strategy and the estimators of the subset mean and the subset standard deviation.

A common feature found in many adaptive models is the computation of the necessary specification adjustments using the sample mean of a population of interest as reference. Nevertheless, when the variation is considered as a function of time, then the sample mean may not be the most suitable estimator to model a long-term drift. For this reason, an alternative estimator is proposed in this work: the cumulative de-noised average.

The uncertainty associated to the measurements made on the subsets of Component 1 has been also incorporated in the proposed control model because it affects directly the estimation of the adjusted tolerances of the matching subsets of Component 2.

One of the topics that often receives less attention when discussing adaptive models is the controller's ability to trigger the necessary specification adjustments promptly. However, since the sequence of measuring-computing-triggering-adjusting takes time, unless the conveyors stop for a while after the inspection of every subset, response delays should be taken into account. Therefore, the analysis of response delays on the controller performance was considered a matter of interest that deserved to be included in this chapter.

The challenge of the multi-component assembling was also addressed in this chapter. Since SFFCM does not depend on any selection-based assembling technique but on the separation of the system in two subsystems, the multi-component assembling problem can be always reduced to the assembly of two subassemblies that play the role of the feeding and the controlled subsystem respectively.

The eventual implementation of SFFCM in a parallel manufacturing scheme was also explained. The configuration proposed to approach the offset problem is based on several statistical models to predict the evolution of the drift and thus, to overcome the offset problem. Three different predictive algorithms were presented: the first one is based on the last measured sample mean, the second is based on a robust regression algorithm and the last one is based in the dynamic construction of polynomials of second order. In the case of the sample standard deviation, the prediction is based on the repetition of the last measured value.

Finally, modified configurations that consider the contribution of additional feedback loops, internal and external, to monitor the subsystems' outputs are explained. In the first case, the controlled Subsystem B can be fed simultaneously with data coming from the feeding Subsystem A (feed-forward loop) and with data coming from the system's output (feedback loop). In the second case, instead, the feeding Subsystem A can be monitored and theoretically controlled by means of triggering parameter adjustments when the variation reaches or goes beyond the warning levels.

4. DYNAMIC ASSEMBLING SIMULATION SOFTWARE

Chapter Highlights

- Introduces the Dynamic Assembling Simulation Software (DASS)
- Describes DASS modules and features
- Explains DASS algorithms

4.1. Introduction

The nature of the innovative assembly technique, based in SDSM and SFFCM, proposed in this thesis to deal with the high variation problem demanded the development of specialized software to carry out simulations of assembling experiments.

The Dynamic Assembling Simulation Software (DASS) was conceived as a modular solution that allows a complete customization of the setting parameters and the specification of the components to be assembled. Thus, a wide range of different scenarios and experiments can be simulated under specific conditions.

Besides the numerical results of the simulated experiments, DASS offers a complete set of charts and comparisons to help users visualize results in the easiest possible way. Especially attractive are the 3D plotting and the modules to created animated movies that make possible to visualize the final assemblies from different angles.

With DASS it is possible to define multiple scenarios in the setting file to simulate and to replicate them as many times as desired without user interference. This is particularly helpful to obtain comparison charts and to make decisions when performing trial and error experiments.

Since the proposed SDSM and SFFCM require extensive use of operations with vectors and statistical functions, DASS was completely developed using MATLAB R2009b for Windows to take full advantage of the available built-in functions and tool-boxes.

4.1.1. Overview

The goal of this chapter is to describe the modules and functionalities implemented in DASS and to explain in detail some of its mayor algorithms.

Chapter Goals

- Introduce the simulation software DASS and explain the information workflow.
- Explain the algorithms of the most important modules of DASS.
- Explain the strategy to maintain the performance during heavy simulation regimes.

4.1.2. Background

MATLAB is a well known development environment in scientific computing. It counts with extensive libraries and built-in functions that are ready to be parameterized and used. In addition to that, MATLAB offers a generous spectrum of features to manipulate vectors, which facilitates enormously the programming task and helps develop efficient code.

DASS was developed using a combination of two classical software methodologies: waterfall and incremental prototyping [Pre 09 ch.2] (Figure 4-1). As to guarantee the flexibility of the code, all the modules of DASS are fully encapsulated so that any modification to the inside code will affect only one module. MATLAB function-based coding enforces this practice.

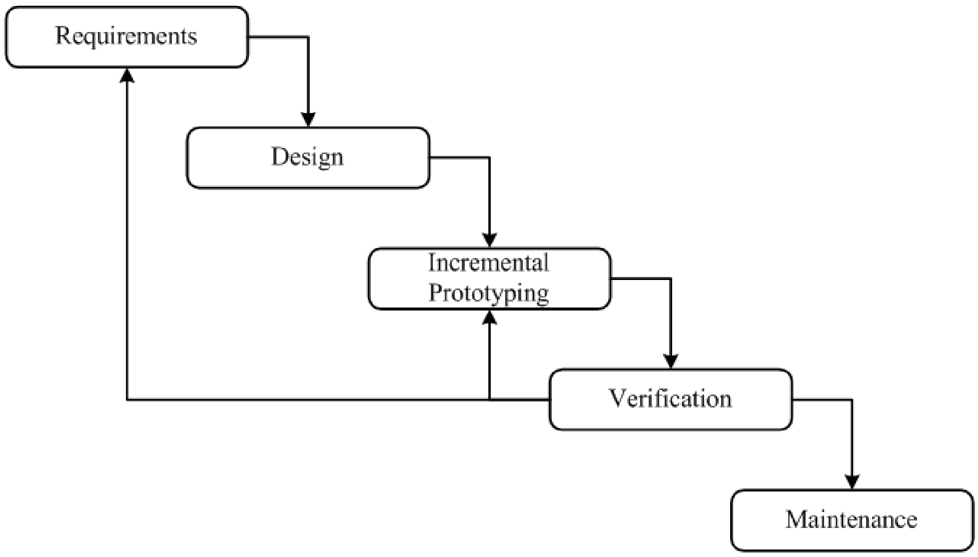


Figure 4-1. Software development methodology: waterfall and incremental prototyping.

4.2. Dynamic Assembling Simulation Software (DASS)

DASS comprises a collection of modules that run in MATLAB. DASS retrieves its configuration and parameters from specific files defined for this purpose. They are the software's input. The output consists on a collection of plots, histograms, comparison charts, MS Excel files and tables with the resulting data (Figure 4-2). In addition to that, DASS is featured to produce 3D plots and to create animated movies to visualize the final assemblies.

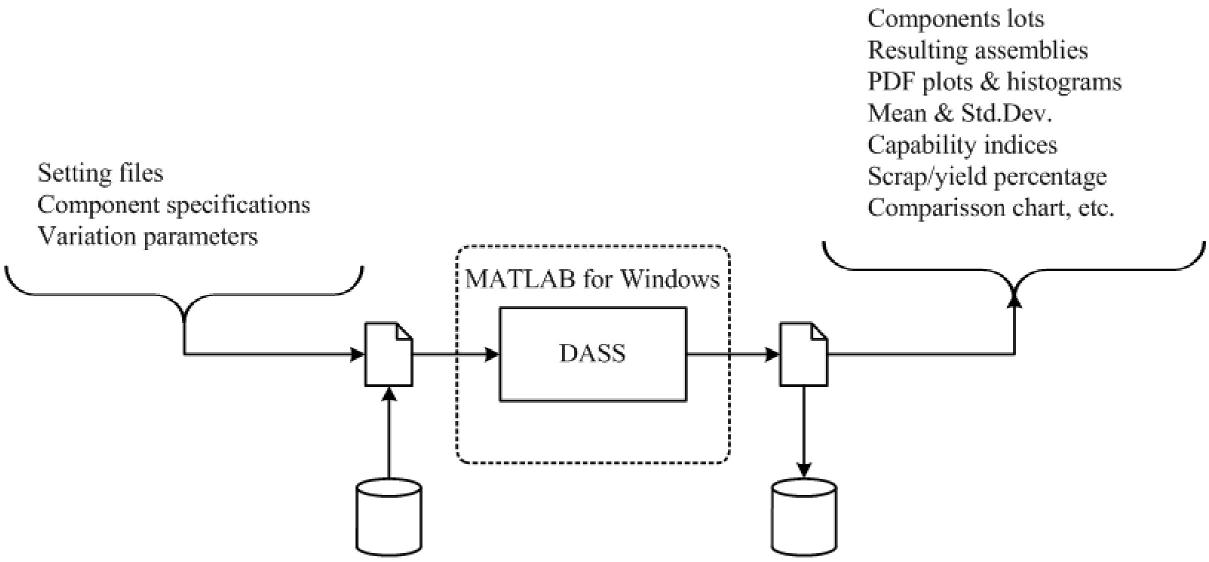


Figure 4-2. DASS inputs and outputs.

4.2.1. DASS Modules

DASS modules are featured to perform specific tasks. Whereas some of them are part of the DASS-core; others perform accessory functions like plotting or managing counters (Figure 4-3).

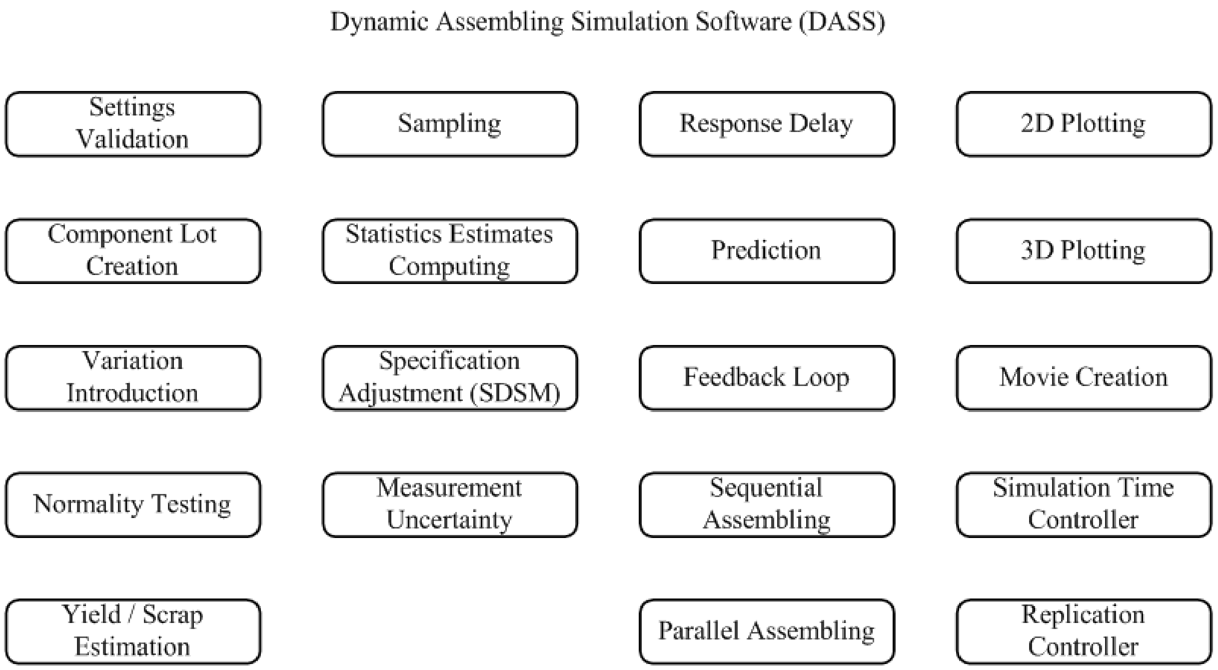


Figure 4-3. DASS modules.

4.2.2. DASS Information Workflow

The way in which DASS modules interact with one another is shown in the software's information workflow (Figure 4-4). This diagram is particularly useful to acquire a good level of familiarity with the software without having a deep understanding of it.

Though everything is already defined in the setting files, several important alternatives or bifurcations, take place along the way. The most important are the control model and the production schemes. While in the first case it is possible to enable the complementary feedback loop, in the latter case it is possible to simulate a parallel production layout by means of activating the offset delay.

Logically, for the sake of clarity, most of the underlying inner working is not shown in this high-level workflow. A deeper level of detail will be given as the chapter progresses.

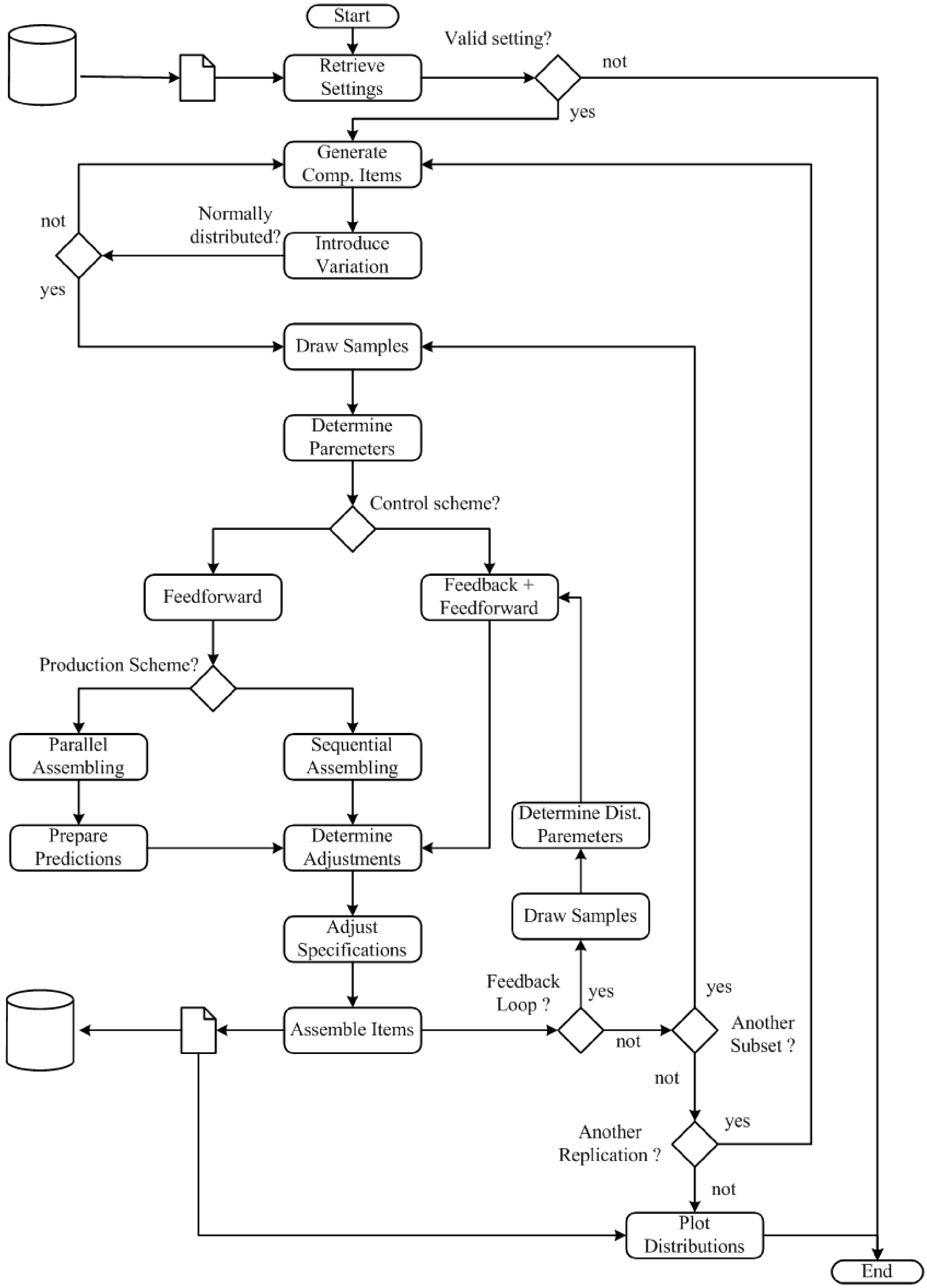


Figure 4-4. DASS workflow.

4.2.3. Validation of Setting Files

The first task performed by DASS is a full validation of the input files, including the existence of the files and the correctness and completeness of their content.

Some of the validations are: field type and completeness, and meaningfulness of the parameters' values. For example: the inspection must be a number larger than 0% but not larger than 100%, the position of the component to adjust has to be a number larger than 1 but not larger than the total number of components, the subset size has to be larger than 2 but less than the lot size, etc (Figure 4-5). An examples of the setting file can be found in Appendix C.

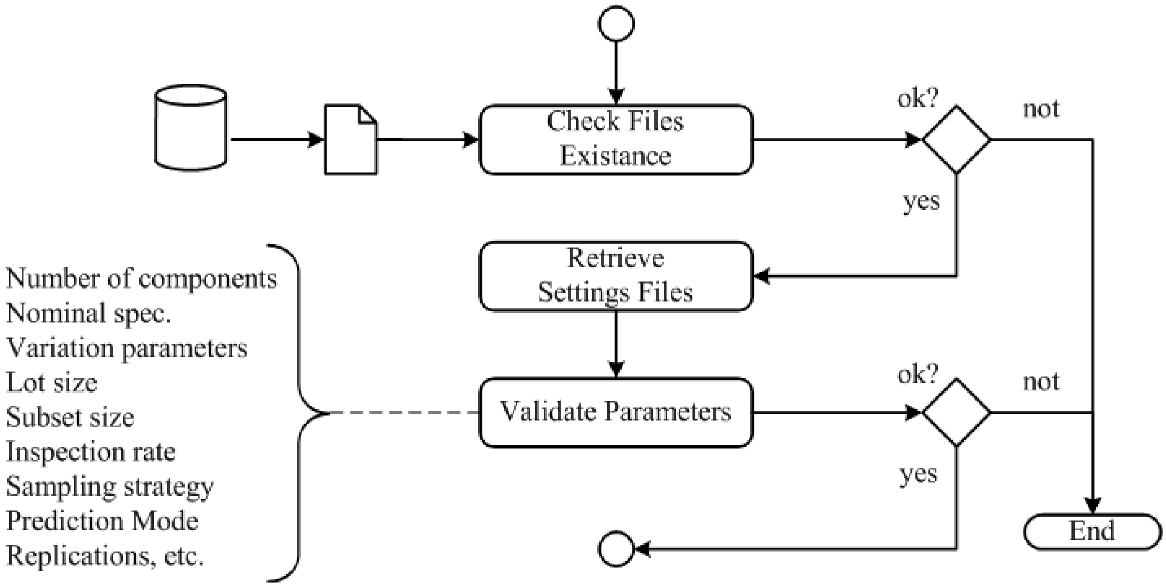


Figure 4-5. Validation of setting files

4.2.4. Generation of Components' Lots

After the validation is complete DASS will be ready to run. According to the specification retrieved from the component's specification file, the corresponding lots are generated. Table 4-1 shows an example of the data contained in this file.

Table 4-1. Example of Component Specification File

	Target	Tolerance	Mean	Std.Dev.
Component 1	10.00	0.58	9.75	0.15
Component 2	10.00	0.58	9.85	0.20
Component 3	10.00	0.58	9.95	0.15

There are two alternatives to generate the lots, simple generation of random numbers or generation by Monte Carlos simulation. Whichever the preference, it can be set in the setting file. To ensure that a new set of numbers is generated in every replication, proper random seeding sequences have been coded.

Depending on the size of the lot, and because of the randomness of the generation, it might be the case that the set of numbers does not have either the exact desired mean or the exact standard deviation indicated in the specification file. To prevent this situation, a specific loop has been coded (Figure 4-6).

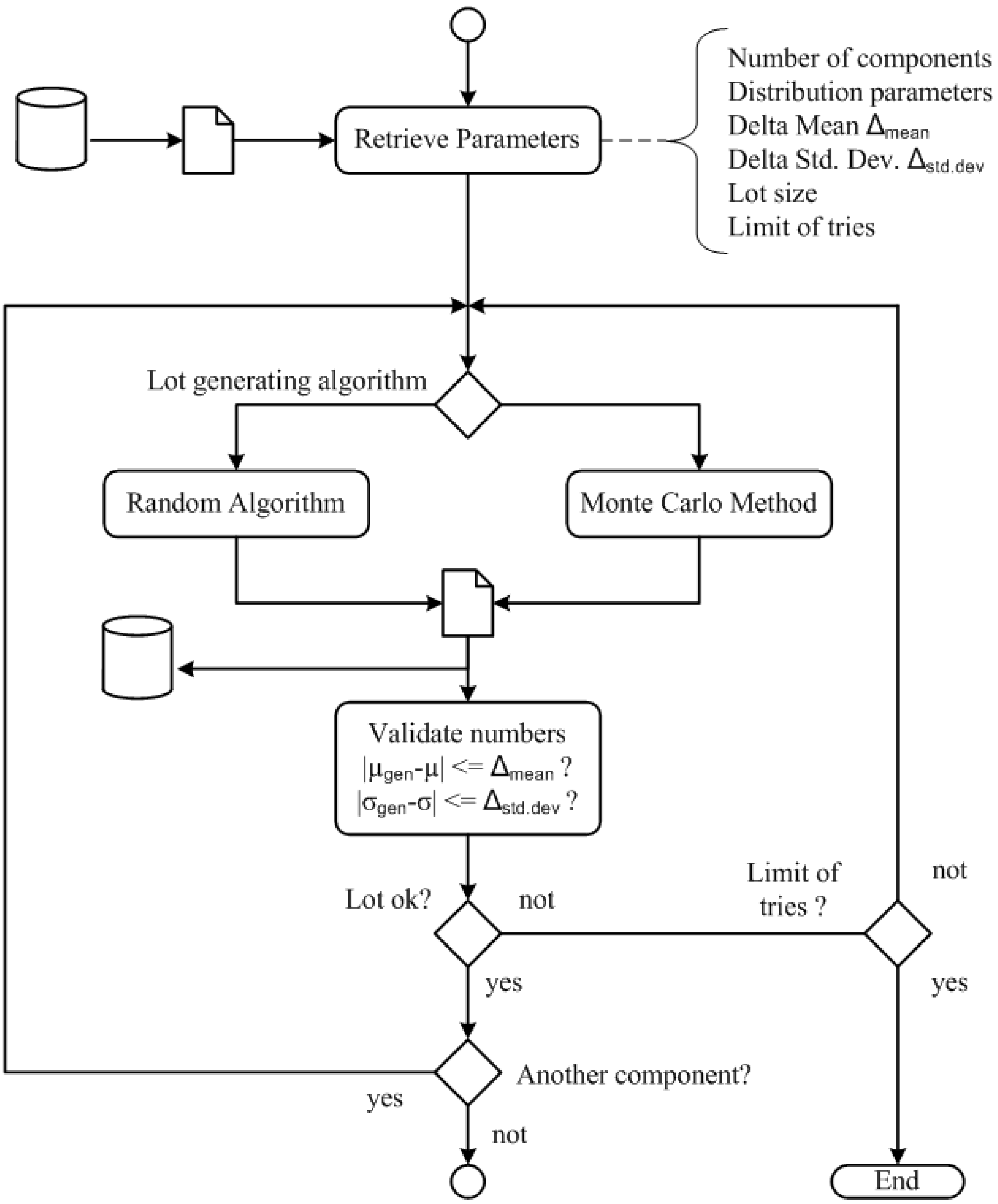


Figure 4-6. Generation of components' lots.

4.2.5. Superposition of Variation on Components' Lots

The importance of the variation and its evolution over time has been already explained and emphasized in previous chapters. DASS allows the user to define freely the type of variation to be simulated. However, as it has been explained earlier, the variation should have a detectable long-term drift. In Appending C, examples of the superposition of different types of variation patterns such as trends and oscillations are presented.

The challenge strives in introducing the combined effect of random noise, trends and oscillations in a lot whose characteristic of interest, in this case the length, is normally distributed and to keep the lot mean μ and lot standard deviation σ unaltered. To do it, a good starting point is to have a look at definition of the sample variance (equation 4-1).

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2 \qquad (4\text{-}1)$$

where μ is the mean and N the population size. Since $(x_i - \mu)$ quantifies the distance between every point of the sample and the mean, extending or shortening these distances will produce an alteration of the variance and thus, a modified standard deviation.

The introduction of the variation into the original lot will undoubtedly produce a change in μ and σ. Therefore, it is necessary to find a way to get them back to their original values afterwards. Let σ_{ini}^2 be the variance of the original lot and let σ_{var}^2 be the variance of the lot after the introduction of the combined variation. Then, the only operation needed to restore the original values is to multiply both sides of the equation (4-1) by $(\sigma_{ini}/\sigma_{\mathrm{var}})^2$. In simple words, the distance between every point of the modified lot and the mean will be either enlarged or shortened by the ratio $(\sigma_{ini}/\sigma_{\mathrm{var}})$ so that the original value can be restored. Restoring the modified mean value only requires a simple correction of the mean shift to get the mean back to its original state.

The variation introduction process is shown in Figure 4-7. The particular case of a multi-component assembling simulation where the position k of the component to be adjusted is between 2 and N_c-1, being N_c the total number of different components, will be explained in detail in latter sections. A full example of variation introduction including normality test is given in Appendix C.

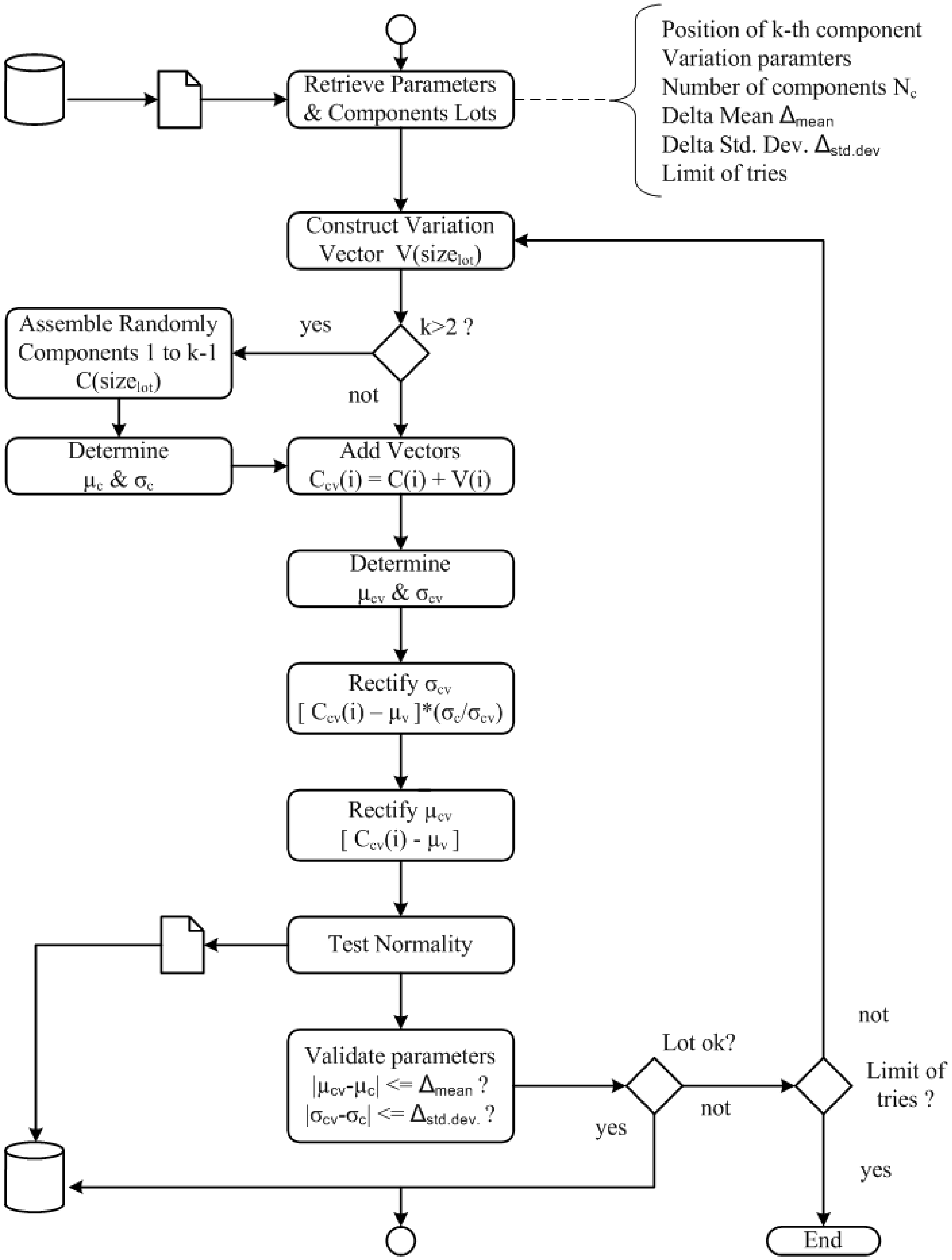


Figure 4-7. Superposition of variation on components' lots.

4.2.6. Sampling Strategies

The way in which items are drawn for inspection can be performed according to a completely simple random selection or according to a systematic random selection. The difference, already explained in Chapter 3, basically resides in the selection at fixed intervals performed in the systematic case (Figure 4-8).

DASS offers the possibility of repeating the same selection pattern in all subsets or changing it completely for each one. This might be very helpful to diminish the risk of "sampling error" due to the possible presence of an oscillatory pattern in the variation.

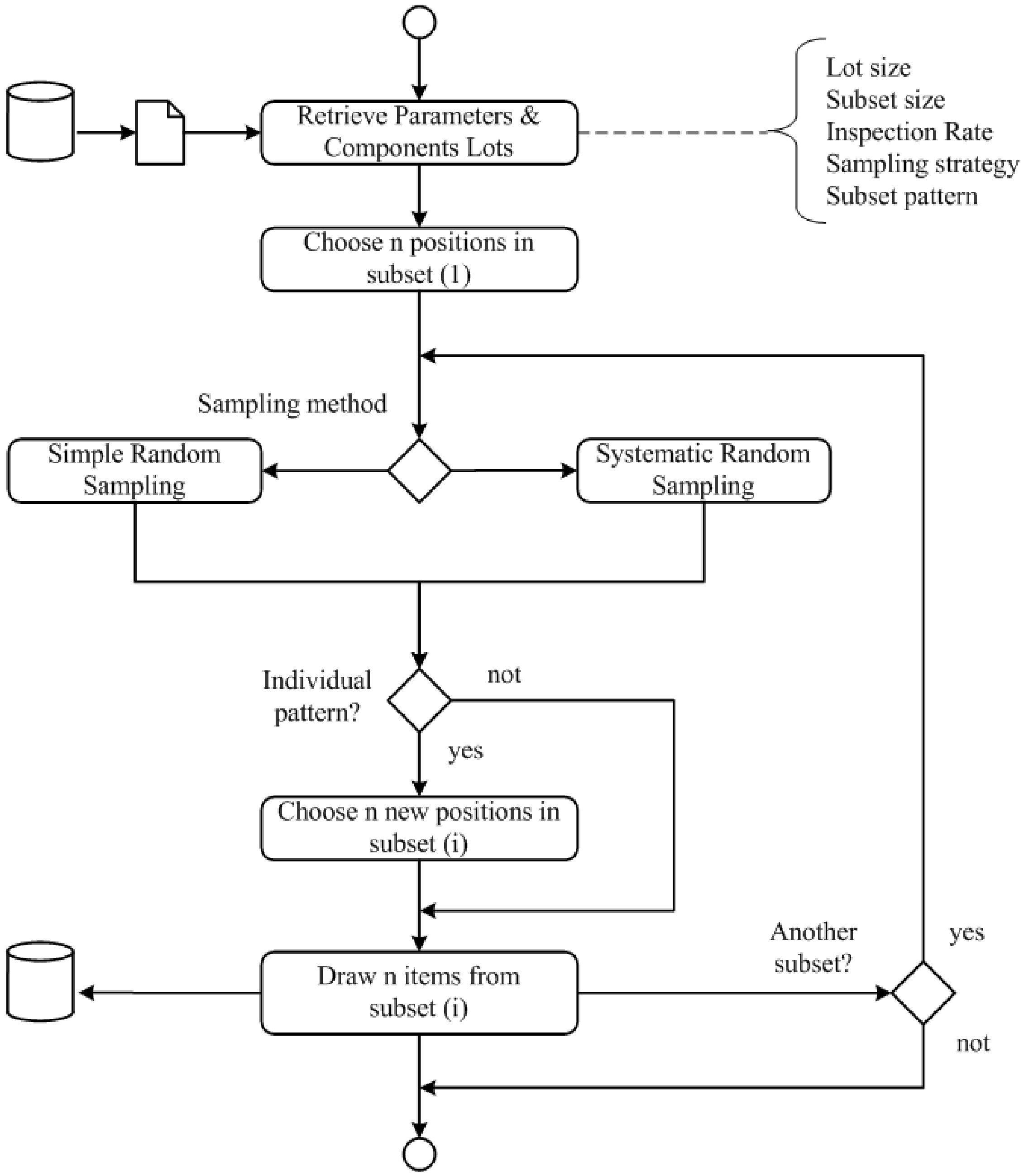


Figure 4-8. Sampling methods.

4.2.7. Central Tendency Measure

Although common in adaptive assembling techniques, the use of the sample mean to calculate the necessary adjustment to the target of a given process is limited by its lack of memory. Indeed, it has been already explained that while the sample mean only considers the data retrieved from the last inspected sample, the CDNA uses data from previous subsets.

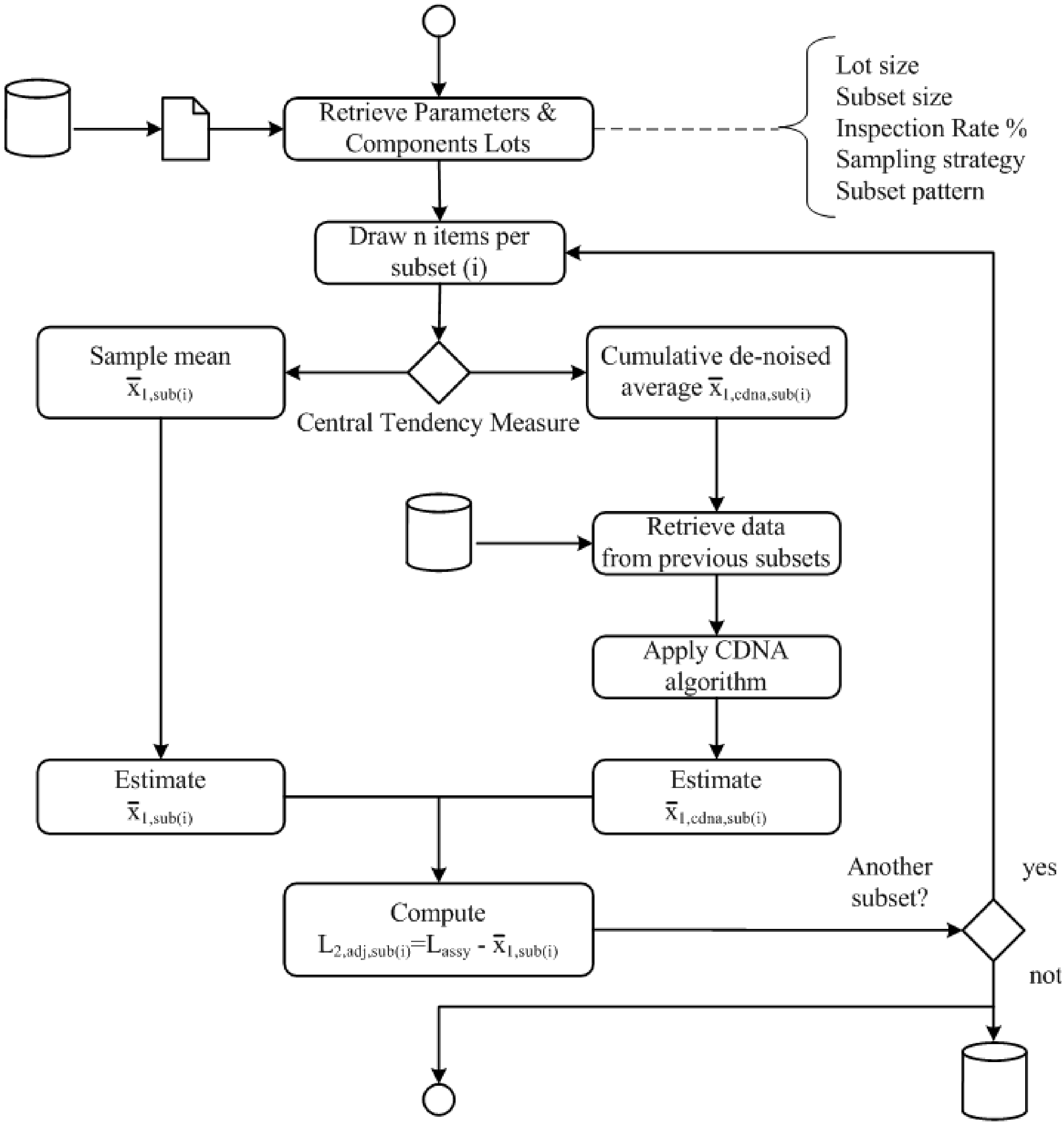


Figure 4-9. Sample mean and cumulative de-noised average (CDNA).

By default, DASS is prepared to use the sample mean as the basic central tendency measured. However, DASS offers a more sophisticated alternative: the cumulative de-noised average (CDNA). The main difference between the sample mean and CDNA is the use of the available data in the latter case (Figure 4-9).

The resulting value, either the sample mean or CDNA, is used then to determine the adjusted target that has to be applied in the subsequent adjustment. The specific steps to compute CDNA are shown in Figure 4-10. Further details about the wavelet-based de-noising algorithm can be found in Appendix A.

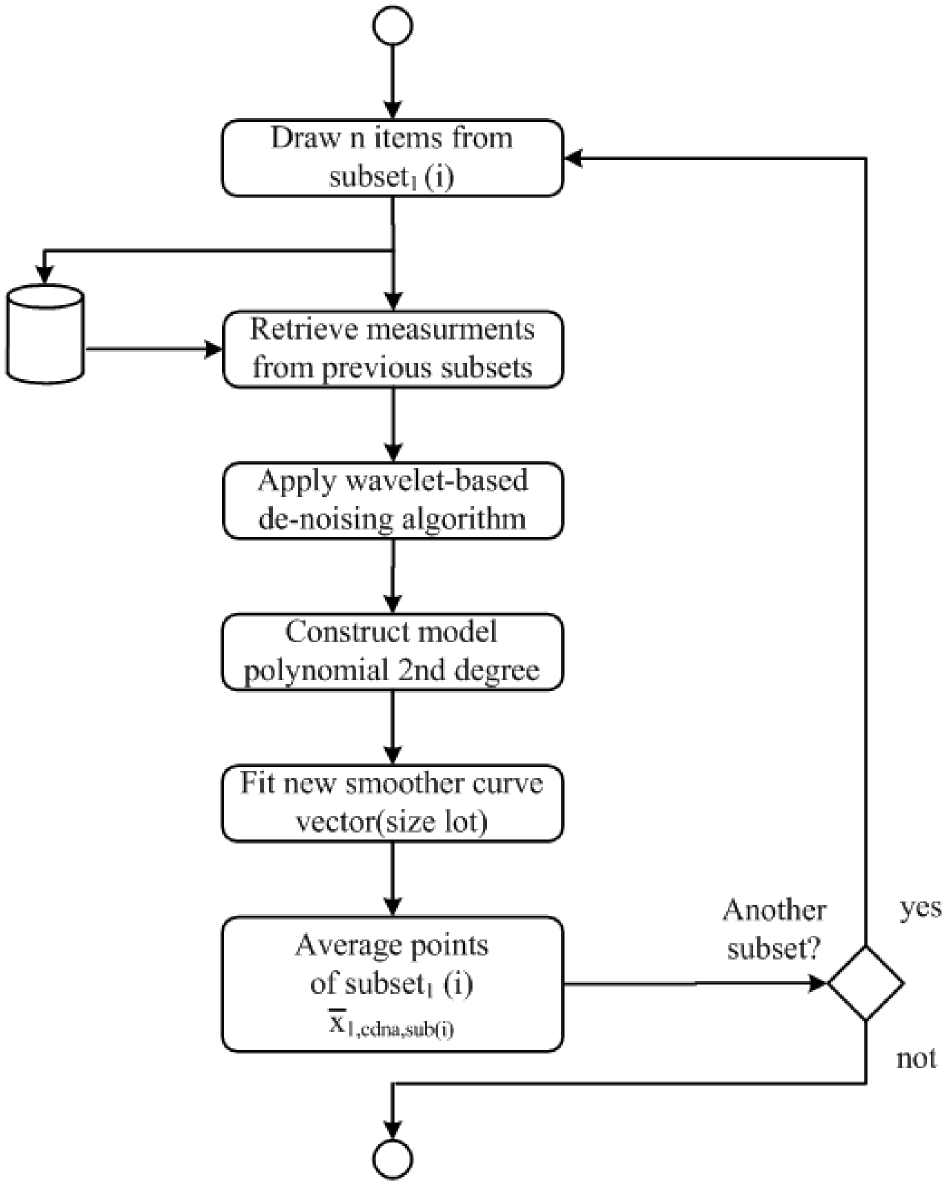


Figure 4-10. Computation of the cumulative de-noised average (CDNA).

4.2.8. Measurement Uncertainty

As explained in Chapter 3, the magnitude of the measurement uncertainty has direct influence on the value of the adjusted tolerances. DASS is featured to include it in the configuration file of the experiments to be simulated (Figure 4-11).

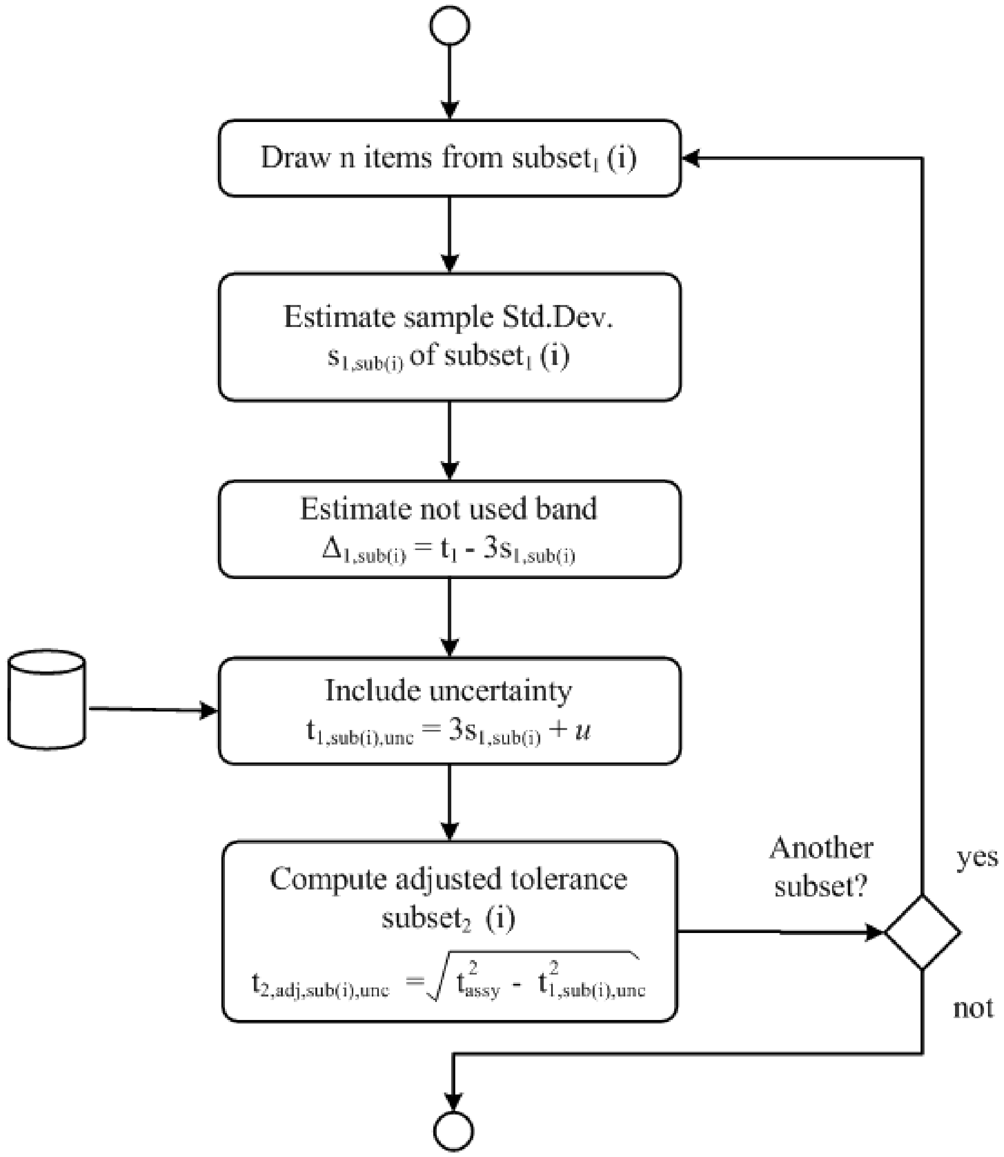


Figure 4-11. Consideration of the measurement uncertainty.

4.2.9. Complementary External Feedback Loop

A radical alternative to the proposed SFFCM is the inclusion of an additional complementary external feedback loop to monitor the systems' output, i.e., the length of the resulting assemblies. DASS is ready to work either with the feed-forward configuration alone or with a configuration that combines a feed-forward and a feedback controller.

In addition to the data gathered by the feed-forward control, the feedback controller helps estimate the mean shift of the resulting assemblies so that it can be included in the computation of the target of a subsequent subset of items (Figure 4.12).

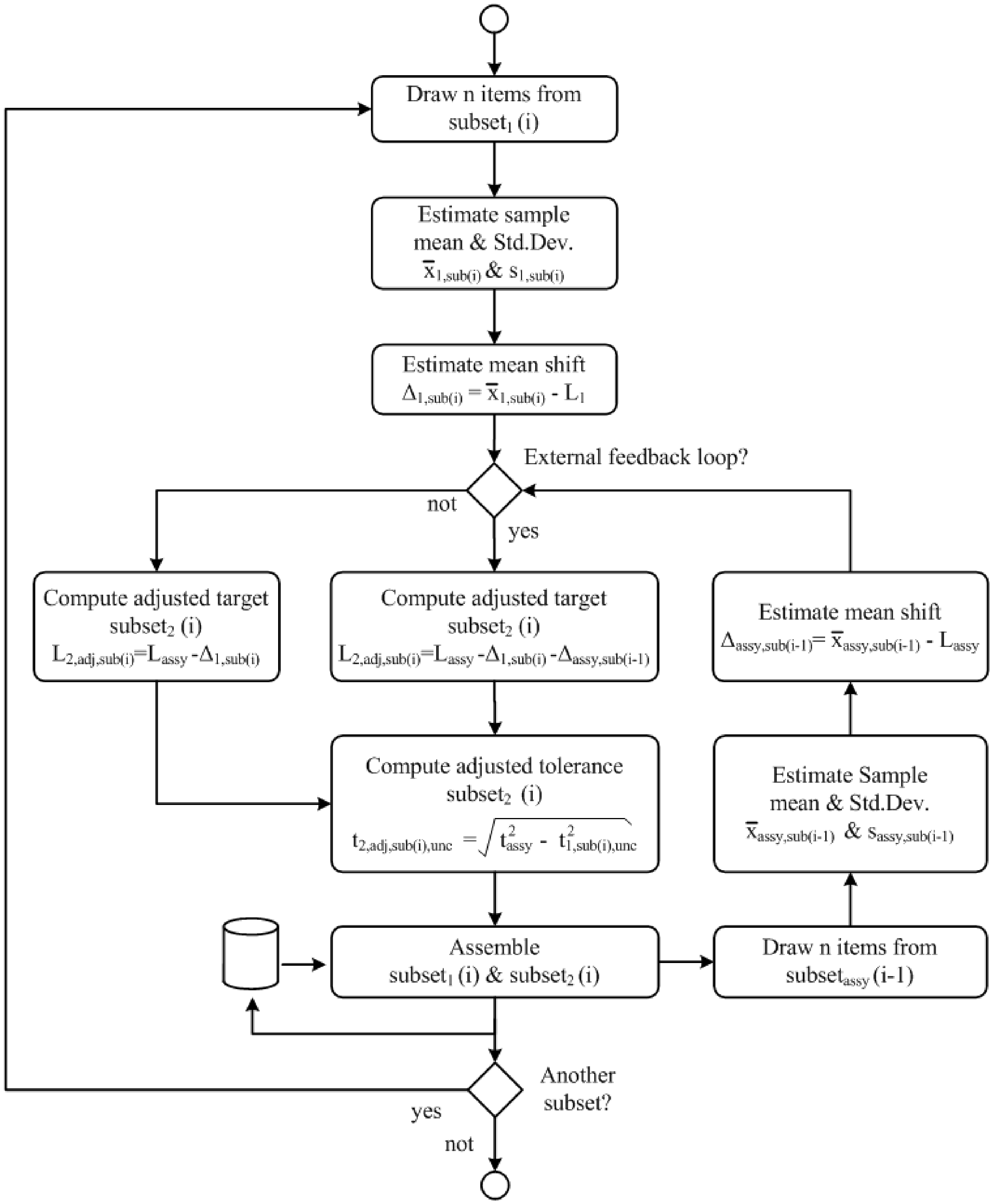


Figure 4-12. Complementary external feedback loop.

4.2.10. Multi-Component Assembling

One of the most attractive functionalities of DASS is the ability to handle multi-component assembling problems. As a matter of fact, it is SFFCM that lends itself for this sort of challenges thanks to the principle of dividing the system in two subsystems. Thus, independently of the number of components involved, SFFCM only has to deal with a feeding and a controlled subsystem.

Let N_c be the total number of components to be assembled, and k the position of the component whose target and tolerance are meant to be adjusted. The value of k defines the boundaries of the subsystems. The alternatives are summarized in Table 4-2.

Table 4-2. Different Values of k

Position k	Feeding Subsystem	Controlled Subsystem	Adjusted Component
$k = 2$	Comp. 1	Comp. 2	Comp. 2
$2 < k < (N_c – 1)$	Rnd. Assy [1..(k-1)]	Rnd. Assy [k.. N_c]	Comp. k
$k = N_c$	Rnd. Assy [1..(N_c-1)]	Comp. N_c	Comp. N_c

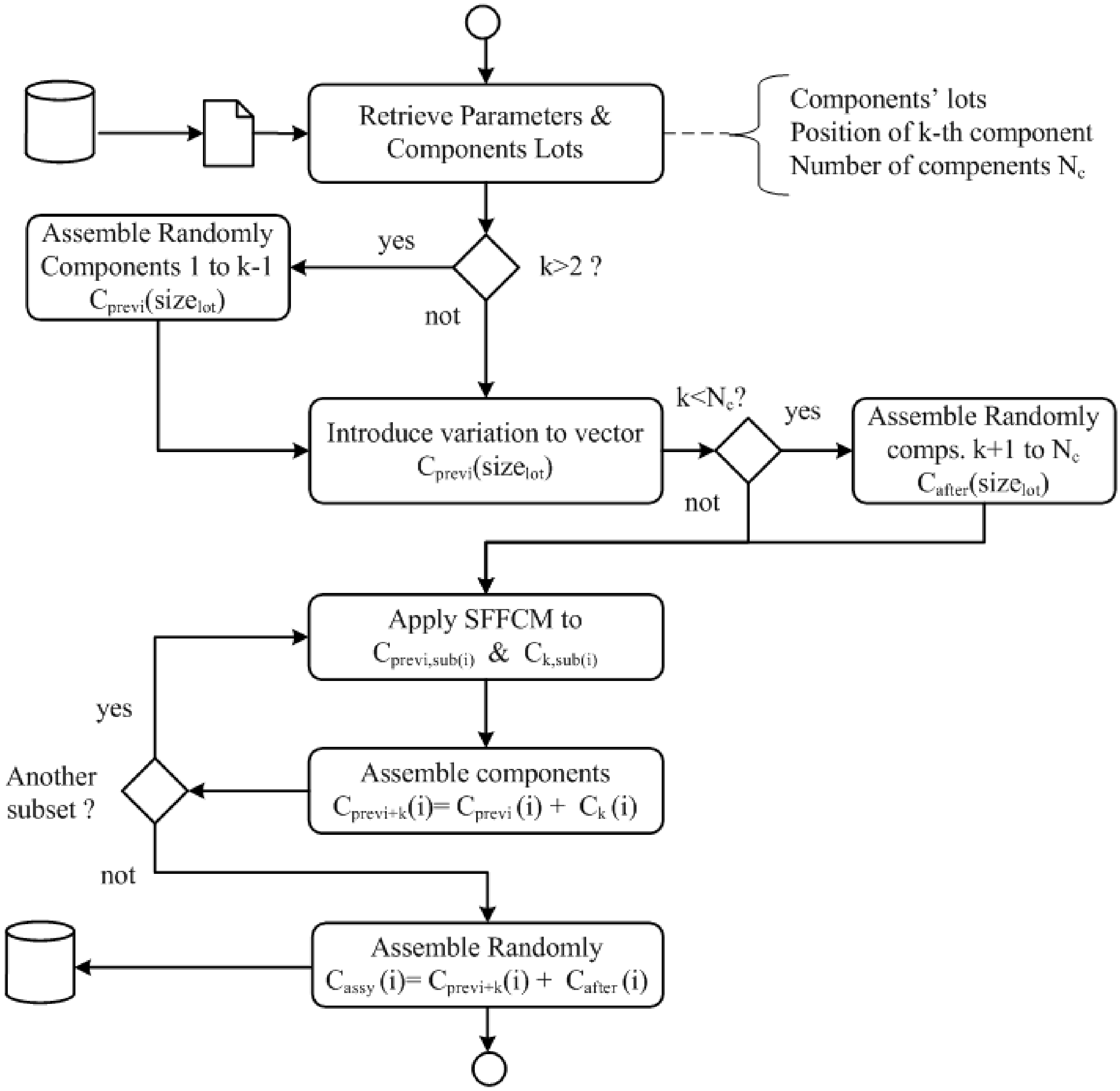


Figure 4-13. Multi-component assembling strategy.

The most complex scenario occurs when k is a number larger than 2 but less than N_c. In this case, components 1 to (k-1) are randomly assembled to form the subassembly $C_{prev}(i)$, which corresponds to the feeding Subsystem A. Components (k+1) to N_c are also randomly assembled to form the subassembly $C_{after}(i)$. SFFCM is then applied to mate the subassembly $C_{prev}(i)$ of components 1 to (k-1) and the component in position k, $C_k(i)$. The resulting subassembly $C_{prev+k}(i)$ is then randomly assembled to the subassembly $C_{after}(i)$ of components (k+1) to N_c (Figure 4-13)

DASS is enabled to perform a full simulation of a multi-assembling experiment and deliver a comparison chart with the results of all possible values of k in the range [2..N_c] using the same set of numbers generated either randomly or by a Monte Carlo simulation. This is particularly useful to determine the position k where the implementation of SFFCM optimizes the efforts.

4.2.11. DASS Performance

Since DASS has to carry out complicate algorithms and operations with vectors, its performance, measured in terms of the simulation time, is a relevant factor when the simulated experiments are replicated massively between 500 and 700 times. Since such heavy computing load consumes gradually great part of the computer's processing power and memory, these limited resources have to be managed efficiently.

The first measure to help keeping the high performance of DASS is to disable all the 2D and 3D plotting features. Besides that, a strategy consisting on the full deletion and release of memory after each replication was implemented. Under this mode, relevant data and counters have to be previously saved in external files and then recovered whenever a new replication is initiated (Figure 4-14).

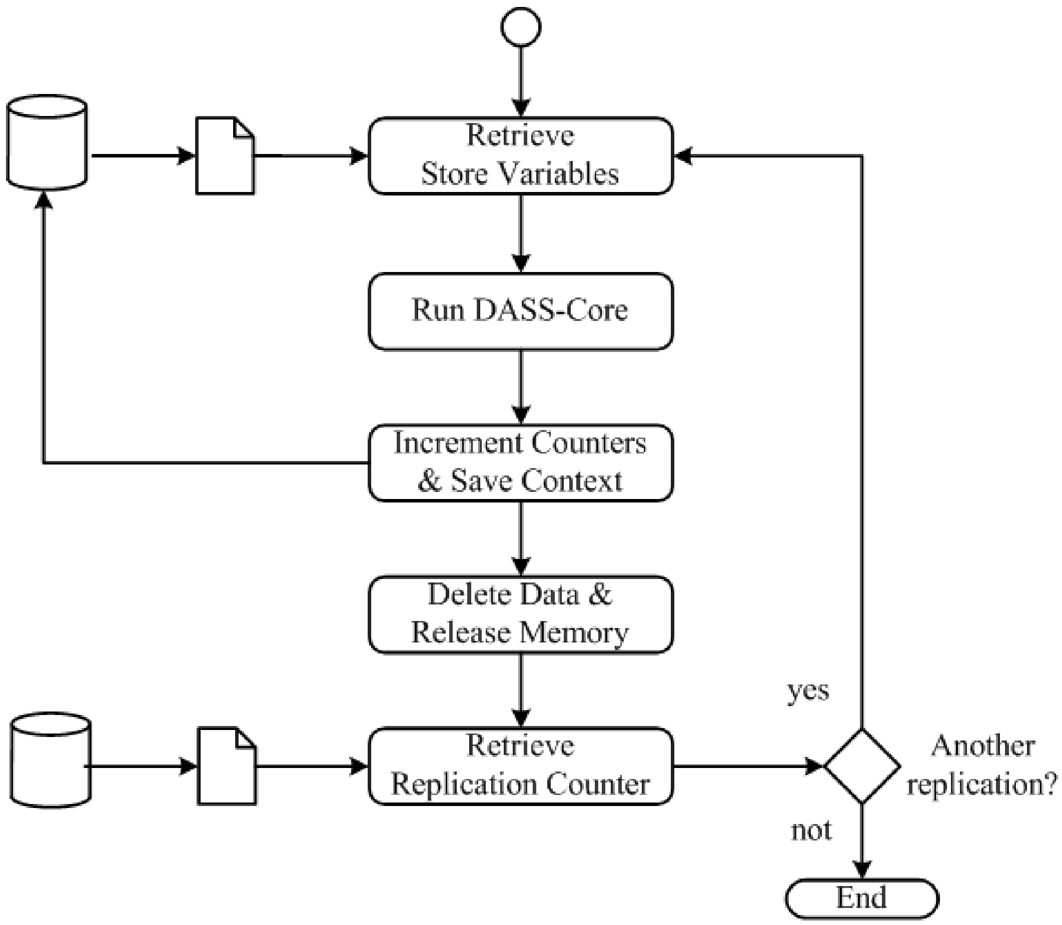


Figure 4-14. Memory release strategy for massive replications.

4.3. Chapter Summary

The first sections of this chapter presented the reasons and advantages that made of MATALB the selected alternative to develop DASS. Among others, the number of built-in functions and the capabilities to perform operations with vectors can be mentioned.

DASS was developed using a combination of the well-known software methodologies waterfall and incremental prototyping. It consists of a collection of modules that perform specialized tasks.

In the middle section of the chapter, some of the key features and modules of DASS are presented and explained in detail. First, the high-level information workflow of the software is presented to help users get familiar with DASS. Then, specific functionalities were explained. Among others: the generation of the components' lots, the introduction of the combined variation effect on the characteristic of interest, the sampling strategies, estimation of the sample mean as the central tendency measure and the alternative cumulative de-noised average (CDNA), and the inclusion of the measurement uncertainty.

Special attention deserved the explanation of the modules corresponding to the complementary feedback loop and to the multi-component assembling. In the first case, it was shown that DASS is ready to work under two configurations: feed-forward loop alone and feed-forward loop complemented by a feedback loop. In the second case, the strategy to approach multi-component assembling problems consists in reducing the problem to the assembling of two subassemblies that play the roles of the feeding Subsystem A and the controlled Subsystem B. These subassemblies are the result of performing a randomized assembly of their respective components.

The last part of the chapter is dedicated to the strategy implemented to help DASS maintain the performance during the simulation of massive replications. The idea is based on the release of the processing resources and memory after each replication. Relevant data and counters are saved in external files that have to be recovered whenever a new replication is initiated.

5. SIMULATION RESULTS

Chapter Highlights

- Describes the simulated experiments.
- Presents the simulation results.
- Explains and discusses the simulation results.

5.1. Introduction

Since the effectiveness of the proposed SFFCM-based assembling technique depends on the effectiveness of the feed-forward controller, through out this chapter, these two concepts will be used indistinctively.

The result of the assembling process depends on a number of factors that can be classified in three mayor groups: factors belonging with the assembling process, factors related to the limitations of the feed-forward controller and factors that are part of the controller configuration (Figure 5-1).

1. Factors that belong with the assembling process, such as:
    - number of components to assemble,
    - nominal target and tolerance of the components,
    - lot size,
    - mean and variance of the components' lots,
    - composition of the variation, and
    - configuration of the assembling lines.

2. Factors related to the limitations of the feed-forward controller, such as:
    - measurement uncertainty, and
    - response delays of adjustments.

3. Factors that are part of the feed-forward controller configuration, such as:
    - subset size,
    - sample size (inspection rate),
    - sampling strategy,
    - estimators of the subset mean and the subset standard deviation,
    - position of the component to be adjusted, and
    - prediction mode in the case of parallel configurations of the production lines.

Since most of the factors mentioned above can adopt different values, the total number of possible combinations might be unmanageable. For this reason, it is necessary to define a strategy to identify those values that produce the best final results.
DASS was designed and developed having all the factors above in mind, and thus, it provides a collection of parameters that are fully configurable to give the experimenter enough flexibility to simulate different scenarios.

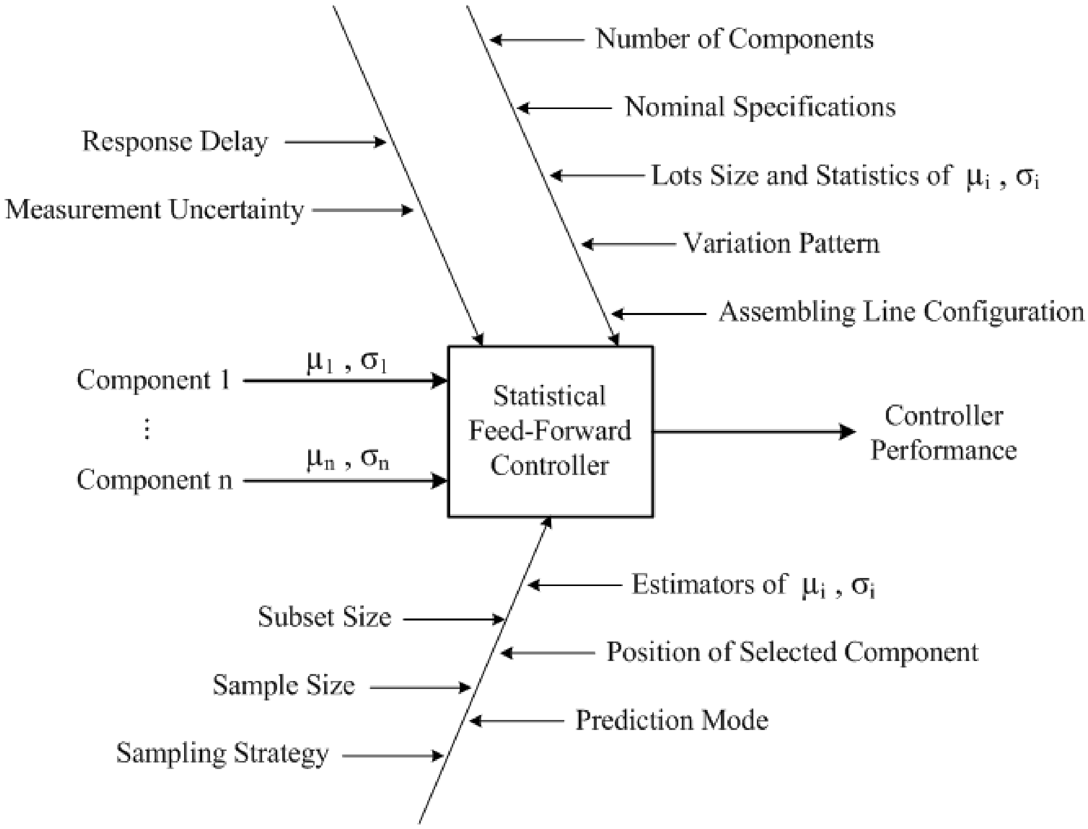


Figure 5-1. Performance of a statistical feed-forward controller.

5.1.1. Overview

This chapter provides the definition, purpose, assumptions, limitations and results of the experiments carried out during this research. The following sections describe the extensive set of computer-based simulations that were performed to quantify the benefits of implementing the proposed SFFCM-based assembling technique in a production environment.

Chapter Goals

- Quantify the influence of individual and combined factors on the system's output.
- Demonstrate the benefits of applying SDSM to allocate tolerances, to increase the capability indexes of non-capable subprocesses, and to assist in adjusting specifications.
- Prove the effectiveness of the proposed SFFCM-based assembling technique in helping produce low variation assemblies made of high variation components.
- Quantify the benefit of using the proposed cumulative de-noised average instead of the sample mean to model and counter the effect of the long-time drift.
- Quantify the impact of response delays in the application of adjustments on the effectiveness of the feed-forward controller.
- Evaluate the effectiveness of SFFCM predictive algorithms on parallel assembling lines.
- Quantify the benefit of complementing SFFCM with an additional feedback loop.

5.1.2. Background

Among the wide range of alternatives, finding the combination of values that makes the feed-forward controller deliver the best results, while optimizing the effort, requires the design of set of experiments to test the controller under specific conditions.

5.1.2.1. Design of Experiments (DoE)

Federer [Fed67 ch.1 p.6] defines the design of experiments (DoE) as a design exercise aimed to gather data from phenomena that have variation. The experiments are intentionally designed to identify the influence of diverse factors on the behavior of the matter of interest. All experimental design may be divided into systematic designs and random designs.

5.1.2.2. Full Factorial Experiment

In a full factorial experiment of two or more factors, each with discrete possible values or levels, the experiment takes on all possible combinations of these discrete values across all the factors. This type of experiments allows studying the effect of each factor as well as the effects of interactions between factors on the response variable. If there are k factors, each at 2 levels, a full factorial experiment would have 2^k runs [NIST/SEMATECH ch.5.3.3.3].

Table 5-1. Runs for a 2^k Full Factorial [NIST/SEMATECH ch.5.3.3.3]

Nr. of Factors	Nr. of Runs
2	4
3	8
4	16
5	32
6	64
7	128

5.1.2.3. Replications

A replication can be understood as the repetition of an experimental condition so that the variability associated with the phenomenon can be estimated. Replication is not the same as repeated measurements of the same item. To replicate means to repeat the empirical operations and to record data that supports the original claim [Osb08].

Fisher [Fis66 ch.4 pp.60-62] identified two purposes of replication. First, it serves to diminish the error and second, it supplies an estimate of error by which the significance of the experimental comparisons can be judged.

According to Federer [Fed67 ch.3 p.70], since variability is almost universal, replication should be practice in nearly all experimental work. The appropriate number of replications for an experiment is determined, among others, by:

1. The degree of precision desired.
2. The amount of variability present in the experimental material.
3. The availability of resources, personnel and equipment.
4. The size and shape of the experimental unit.

The importance of the replications should not be taken lightly because crucial additional information can be only extracted from the data collected after replicating an experiment several times. Kessel et al. [Kes11] discussed in great detail the problem of finding the optimum number of trials when using Monte Carlo Methods.

5.2. Simulation

All the experiments presented in the following sections were simulated with the help of DASS, described in Chapter 4.

To accomplish this chapter's objectives a vast number of specific experiments were defined to provide data about the influence of isolated factors and combination of them on the overall performance of the proposed control model.

In previous chapters it was explained that the effectiveness of proposed feed-forward controller was going to be quantified in terms of certain key parameters of interest, such as the mean and the standard deviation of the resulting assemblies' length. However, besides that, the corresponding variation of these parameters after massive replications has to be analyzed as well. This is a good way to realize if the controller is able to deliver consistent results over time when the experiments are replicated using new lots of components generated either randomly or by a Monte Carlo simulation.

5.2.1. Description of Experiments

For the purposes of this work, the production of certain good or product that is manufactured in lots of one thousand items at the time was simulated. The final product is supposed to be an assembly made of two components whose corresponding production processes are known for delivering items with high dimensional variation.

Before the simulations were carried out, a number of experiments were designed for different purposes. During the simulations, the values of key factors were tried and varied stepwise as to detect the value that delivered the best results in the defined scenarios. All the experiments, for every value of the factors, were replicated at least five hundred times using different components' lots generated using Monte Carlo Methods.

5.2.2. Initial Assumptions

The following assumptions were taken as valid during the simulations:

1. Normality. The lengths of the component items are normally distributed and are statistically independent.
2. No correlation. There is no correlation between the components' lots.
3. Variation superposition. The variation affecting the processes can be separated into a not controllable short-term noise and a detectable and potentially controllable long-term drift.
4. Process stability. The manufacturing processes under study are stable so that they respond to the adjustments without going out of control.

5.2.3. Nominal Specifications and Process Characteristics

While the component nominal specifications and tolerances are defined in the product design phase, perhaps with relative freedom within the limitations imposed by the functional requirements, the mean and standard deviation of the dimension of interest depend on the conditions in which the manufacturing process runs. The initial conditions of the simulations are shown in Table 5-2.

Table 5-2. Nominal Specifications and Process Characteristics

	Length [mm]		Process Characteristics		
	Target	Tolerance	Mean	St. Deviation	C_p
Assembly	30.00	1.00	29.55	0.29	1.15
Component 1	20.00	0.82	19.60	0.25	1.09
Component 2	10.00	0.58	9.95	0.15	1.29

Since the values of the items' length are independent and normally distributed, the mean and standard deviation of the values of the resulting assemblies' length (Table 5-2) can be computed directly using the following formulae [Bur79 ch.12 p.339], [Dun65 ch.10 p.91].

$$\mu_{assy} = \mu_1 + \mu_2 \tag{5-1}$$

$$\sigma_{assy} = \sqrt{\sigma_1^2 + \sigma_2^2} \tag{5-2}$$

$$C_{p,i} = t_i / 3\sigma_i \tag{5-3}$$

Following the definition of SFFCM, Component 1 is meant to represent the feeding Subsystem A and Component 2 the controlled Subsystem B. Thus, the target and the tolerance of the latter are the matter of control and adjustments.

5.3. Simulation Results

All the results obtained during the simulation and analyses of every relevant factor are presented in the following pages. Sections are organized according to the factor under study. In every case, the purpose of the simulation and the design of experiments are given.

The results are grouped in four parts. The first two are the average mean and the average standard deviation obtained after completing all the replications. The remaining two are the variation of the mean values and variation of the standard deviation values detected during the replications. In some exceptional cases, additional paragraphs dedicated to the process capability indices are also provided.

Additional explanations and discussion of the simulation results are often provided as to complement both the tables of results and the corresponding plots.

5.3.1. Variable Subset Size

The purpose of these experiments is to quantify the influence of the subset size on the effectiveness of the proposed SFFCM-based assembling technique [Her11-1]. While the inspection rate remained fixed at 20%, the subset size was set to 50, 100, 125, 200, 250 and 500. For every value of the subset size, the simulation of the experiments in Table 5-3 was replicated 500 times.

The first column of Table 5-3 indicates the experiment identifier. Columns 2 and 3 specify the sampling scheme, either simple or systematic random. Columns 4 and 5 indicate whether the sampling pattern is identical for all subsets or different in each case. Finally, columns 6 and 7 indicate which estimator of the subset mean is used. The alternatives are the sample mean and the cumulative de-noised average.

Table 5-3. Design of Experiments for Variable Subset Size

Exp.	Random Sampling		Subset Sampling Pattern		Tendency Measure Estimator	
	Simple	Systematic	Common	Individual	$\bar{x}_{1,sub}$	$\bar{x}_{1,sub,cdna}$
1	√		√		√	
2	√		√			√
3	√			√	√	
4	√			√		√
5		√	√		√	
6		√	√			√
7		√		√	√	
8		√		√		√

Each entry of the Table 5-4 represents the average mean of the values of the resulting assemblies' length after 500 replications. Since every replication simulates the production of 1,000 assemblies, every number in Table 5-4, in fact, summarizes the data of 500,000 trials.

The data contained in Table 5-4 and Table 5-5 may be better visualized in Figure 5-2 and Figure 5-3 respectively. There, it can be seen that the system output is sensible to the subset size since the curves differ clearly from one another. This should not be a surprise since small subset sizes are expected to help model the long-term drift more accurately than large subset sizes because the intervals are shorter.

Table 5-4. Average Mean of the Resulting Assemblies' Length

Exp.	Subset Size					
	50	100	125	200	250	500
1	29.9484	29.9485	29.9493	29.9487	29.9498	29.9465
2	29.9502	29.9530	29.9558	29.9606	29.9682	30.0063
3	29.9489	29.9485	29.9480	29.9485	29.9478	29.9488
4	29.9500	29.9532	29.9569	29.9597	29.9688	30.0082
5	29.9506	29.9496	29.9496	29.9497	29.9503	29.9489
6	29.9519	29.9525	29.9549	29.9608	29.9668	30.0053
7	29.9503	29.9496	29.9487	29.9498	29.9489	29.9514
8	29.9511	29.9519	29.9546	29.9612	29.9671	30.0090

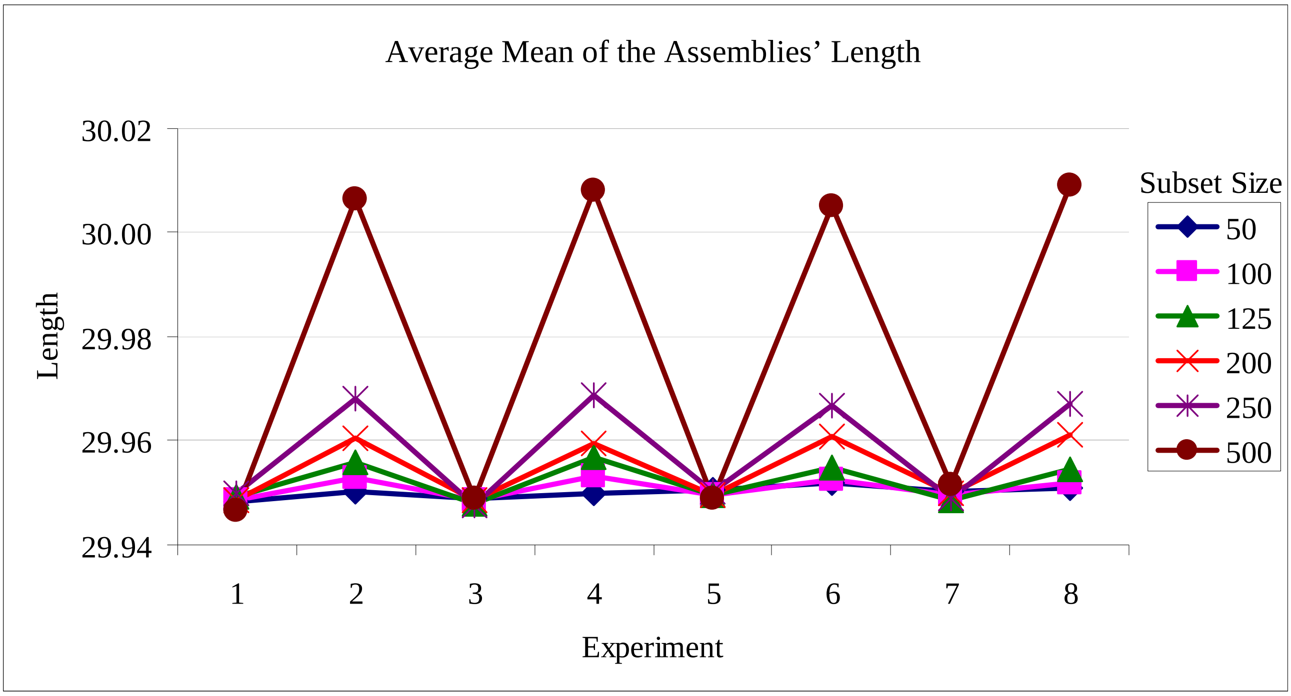


Figure 5-2. Average mean of the resulting assemblies' length.

Table 5-5. Average Std. Dev. of the Resulting Assemblies' Length

Exp.	Subset Size					
	50	100	125	200	250	500
1	0.2430	0.2453	0.2459	0.2489	0.2498	0.2507
2	0.2437	0.2457	0.2478	0.2491	0.2503	0.2585
3	0.2437	0.2456	0.2460	0.2485	0.2492	0.2512
4	0.2435	0.2457	0.2480	0.2487	0.2504	0.2587
5	0.2432	0.2454	0.2458	0.2487	0.2499	0.2507
6	0.2435	0.2462	0.2484	0.2481	0.2499	0.2576
7	0.2435	0.2456	0.2457	0.2488	0.2498	0.2508
8	0.2437	0.2458	0.2480	0.2490	0.2501	0.2578

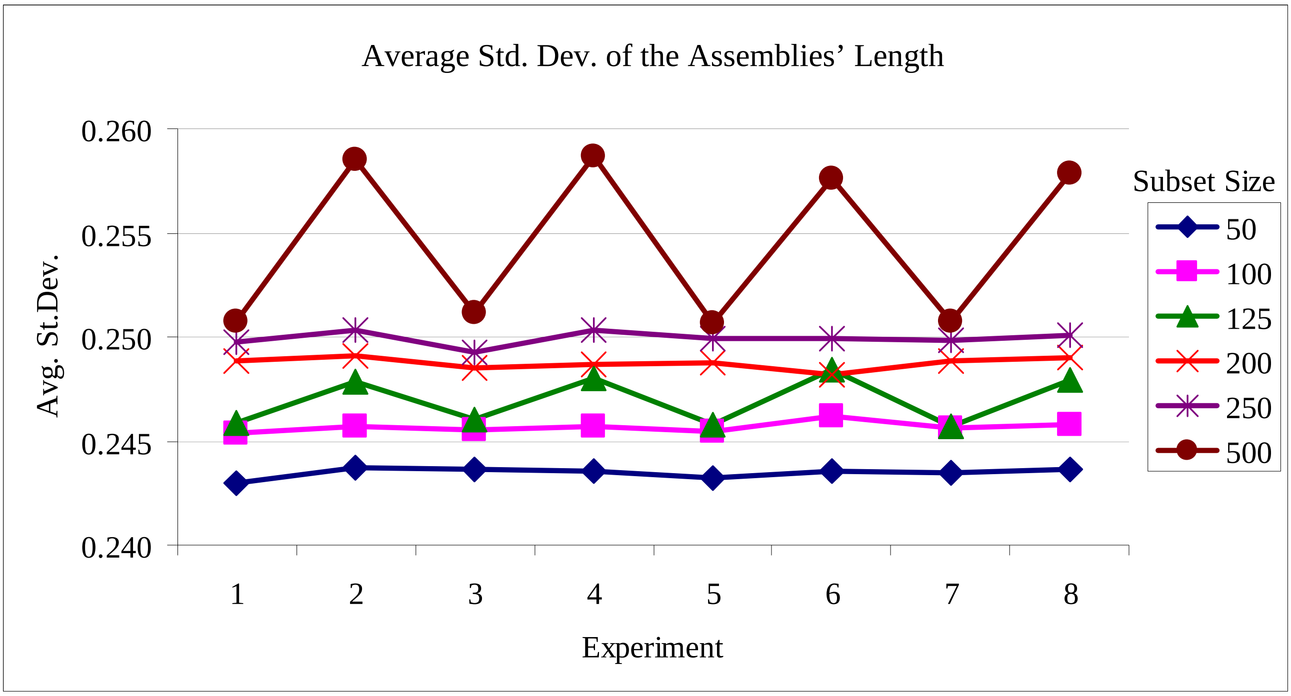


Figure 5-3. Average Std. Dev. of the resulting assemblies' length.

Unfortunately, considering only the data provided by the average mean, Table 5-4, is not sufficient to draw a definitive conclusion. The reason is rather simple. If, for instance, the first replication delivers mean values equal to 25 and 29 for subset sizes S_1 and S_2 respectively, and the second replication delivers mean values equal to 35 and 31. The average mean in both cases would be 30. However, the values of S_2 are undoubtedly preferable because the fluctuation is lower. This kind of information can be retrieved from Table 5-6 and visualized in Figure 5-4.

The plot of the average standard deviation provides valuable information about the controller’s sensitivity to the subset size. Since, in spite of the experiment, small subset sizes produce systematically low standard deviations during the replications, the controller precision improves under such settings.

Table 5-6 and Table 5-7 provide important information about the fluctuation of the individual values of the mean and standard deviation during the replications. Figure 5-4 confirms that the process output is systematically more precise when small subset sizes are used. Although not with the same level of clarity, Figure 5-5 shows a similar tendency.

In summary, it can be argued and demonstrated that the selection of the subset size influences the controller’s ability to improve the assembling process. In this case, the best results were obtained when the subset size was set to values equal or less than 200. Unfortunately, small subset sizes imply more resource-consuming adjustments. It has been already said, that adjustments should be optimized whenever it is possible.

Table 5-6. St. Dev. of the Mean Values of the Resulting Assemblies' Length

Exp.	Subset Size					
	50	100	125	200	250	500
1	0.0087	0.0129	0.0154	0.0188	0.0213	0.0312
2	0.0096	0.0146	0.0170	0.0208	0.0237	0.0345
3	0.0094	0.0122	0.0148	0.0199	0.0221	0.0325
4	0.0095	0.0150	0.0165	0.0219	0.0247	0.0376
5	0.0081	0.0124	0.0142	0.0187	0.0214	0.0304
6	0.0101	0.0154	0.0179	0.0205	0.0232	0.0334
7	0.0084	0.0135	0.0148	0.0191	0.0203	0.0316
8	0.0100	0.0147	0.0171	0.0207	0.0243	0.0347

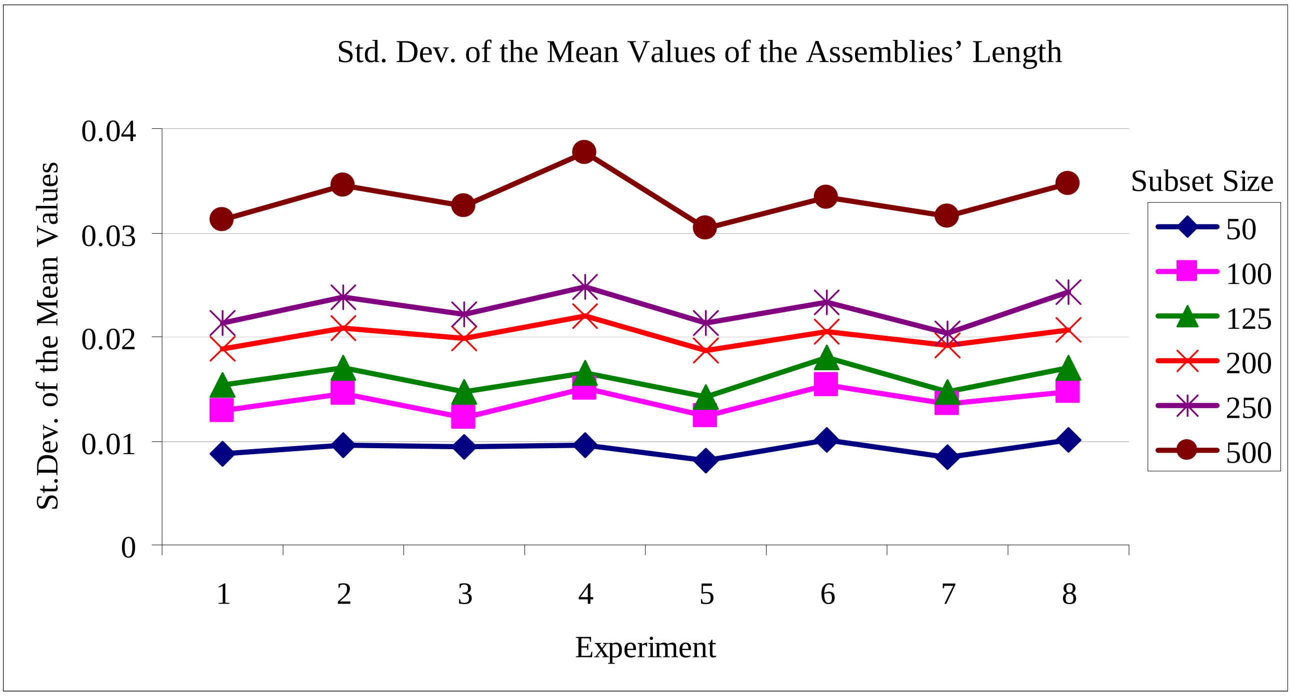


Figure 5-4. Standard deviation of the mean values of the resulting assemblies' length.

Table 5-7. St. Dev. of the Standard Deviation Values of the Resulting Assemblies' Length

Exp.	Subset Size					
	50	100	125	200	250	500
1	0.0051	0.0049	0.0054	0.0054	0.0053	0.0054
2	0.0047	0.0052	0.0054	0.0055	0.0054	0.0072
3	0.0053	0.0051	0.0053	0.0055	0.0056	0.0054
4	0.0051	0.0053	0.0053	0.0056	0.0056	0.0070
5	0.0051	0.0053	0.0051	0.0052	0.0053	0.0057
6	0.0048	0.0051	0.0057	0.0054	0.0057	0.0067
7	0.0048	0.0051	0.0052	0.0051	0.0052	0.0055
8	0.0050	0.0049	0.0053	0.0056	0.0056	0.0066

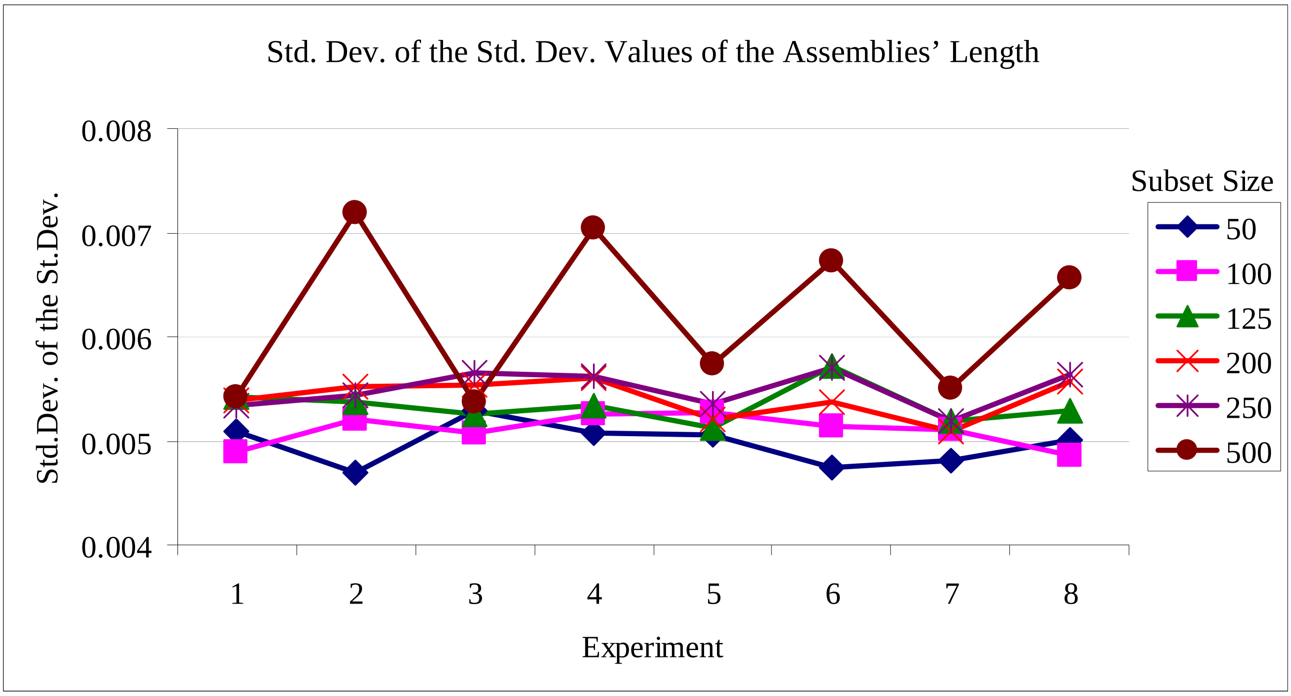


Figure 5-5. Std. Dev. of the standard deviation values of the resulting assemblies' length.

5.3.2. Variable Sample Size

The purpose of these experiments is to quantify the influence of the sample size, or inspection rate, on the effectiveness of the proposed SFFCM-based assembling technique [Her11-3]. While the subset size remained fixed at 125, the percentage of sampled items per subset was set to 5%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, and 90%. For each value of the sample size, the simulation of the experiments in Table 5-8 was replicated 500 times.

Table 5-8. Design of Experiments for Variable Sample Size

Exp.	Random Sampling		Subset Pattern		Tendency Measure Estimator	
	Simple	Systematic	Common	Individual	$\bar{x}_{1,sub}$	$\bar{x}_{1,sub,cdna}$
1	√		√		√	
2	√		√			√
3	√			√	√	
4	√			√		√
5		√	√		√	
6		√	√			√
7		√		√	√	
8		√		√		√

As it was already explained, each entry in the following tables summarizes the data of half a million trials. Table 5-9 and Table 5-10 confirm that, in principle, the system output is sensitive to the inspection rate. This should not be a surprise since more measurements are expected to provide sufficient data to describe better the behavior of the characteristics under observation.

Figure 5-7 helps outdraw some preliminary conclusions. Firstly, the standard deviation found in individual lots is clearly lower when the inspection rate increases. Secondly, large fluctuations seem to vanish when the inspection rates reaches a 30% of the subset size. This means that no additional benefit can be achieved by increasing the inspection rate beyond that level.

The inspection rate is, in fact, one of the key aspects that separate the proposed SFFCM-based assembling technique from classical selective techniques that usually demand 100% inspection to sort the items in the so-called matching categories [Man61]. The optimization of the inspection rate is arguably one of the strengths of SFFCM because, among other benefits, it makes the proposed model suitable for those processes in which a full inspection (100%) is simply not realizable.

Table 5-9. Average Mean of the Resulting Assemblies' Length

Exp.	Inspection Rate (%)									
	5%	10%	20%	30%	40%	50%	60%	70%	80%	90%
1	29.9479	29.9461	29.9506	29.9484	29.9500	29.9508	29.9496	29.9495	29.9493	29.9493
2	30.0147	29.9666	29.9563	29.9521	29.9538	29.9501	29.9503	29.9508	29.9513	29.9510
3	29.9537	29.9484	29.9494	29.9501	29.9500	29.9481	29.9498	29.9500	29.9493	29.9496
4	30.0107	29.9682	29.9554	29.9521	29.9523	29.9527	29.9513	29.9518	29.9513	29.9508
5	29.9476	29.9479	29.9479	29.9497	29.9488	29.9572	29.9543	29.9496	29.9480	29.9488
6	30.0076	29.9625	29.9589	29.9500	29.9488	29.9581	29.9505	29.9464	29.9481	29.9513
7	29.9512	29.9507	29.9454	29.9503	29.9493	29.9554	29.9533	29.9493	29.9481	29.9496
8	30.0098	29.9668	29.9577	29.9495	29.9475	29.9572	29.9504	29.9467	29.9491	29.9515

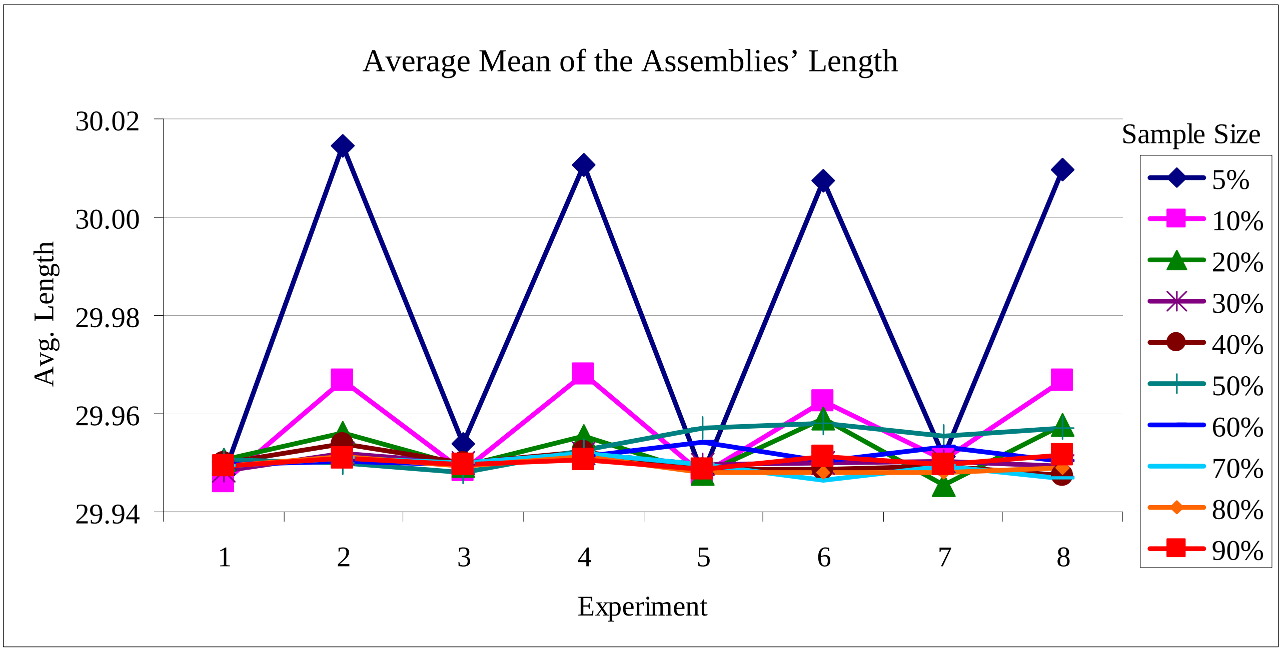


Figure 5-6. Average mean of the resulting assemblies' length.

Table 5-10. Average Std. Dev. of the Resulting Assemblies' Length

Exp.	Inspection Rate (%)									
	5%	10%	20%	30%	40%	50%	60%	70%	80%	90%
1	0.2526	0.2478	0.2460	0.2433	0.2436	0.2436	0.2430	0.2423	0.2431	0.2433
2	0.2538	0.2463	0.2449	0.2437	0.2428	0.2433	0.2436	0.2433	0.2431	0.2425
3	0.2524	0.2478	0.2450	0.2436	0.2433	0.2434	0.2430	0.2420	0.2426	0.2425
4	0.2554	0.2466	0.2442	0.2433	0.2428	0.2434	0.2439	0.2425	0.2427	0.2433
5	0.2523	0.2478	0.2453	0.2438	0.2443	0.2439	0.2430	0.2430	0.2427	0.2423
6	0.2547	0.2472	0.2452	0.2444	0.2437	0.2451	0.2441	0.2426	0.2431	0.2442
7	0.2535	0.2468	0.2449	0.2433	0.2444	0.2447	0.2424	0.2437	0.2423	0.2427
8	0.2549	0.2456	0.2449	0.2447	0.2436	0.2439	0.2432	0.2434	0.2425	0.2427

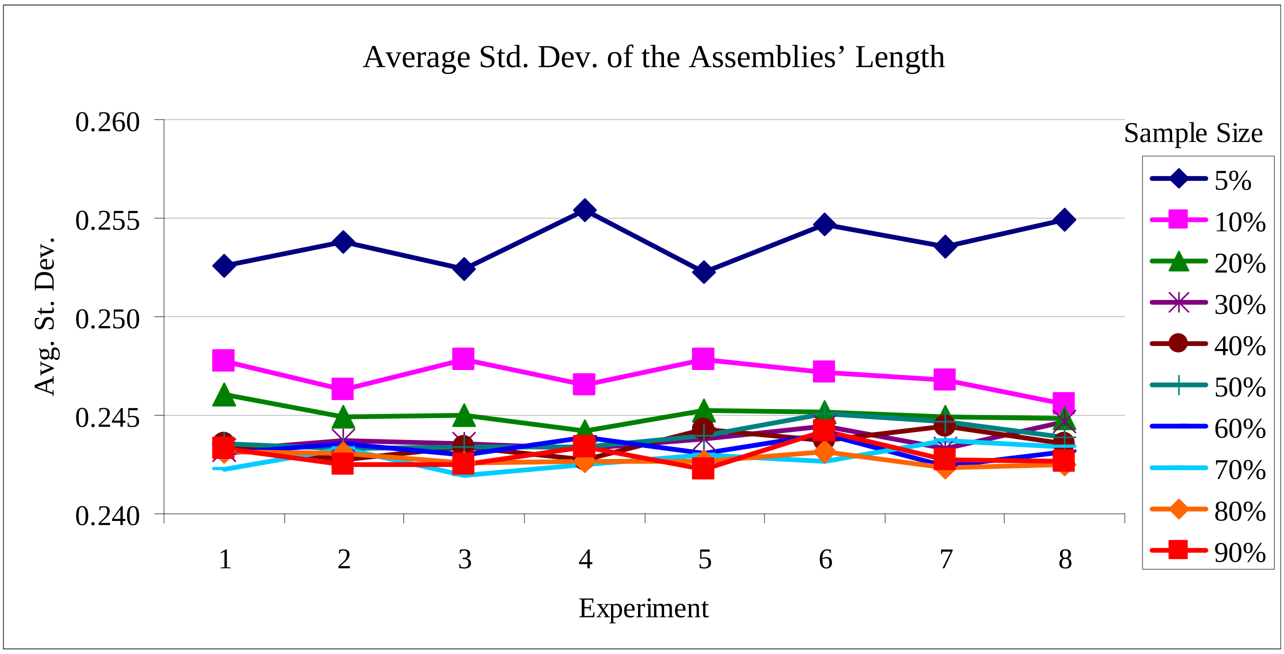


Figure 5-7. Average standard deviation of the resulting assemblies' length.

Table 5-11 and Table 5-12 confirm the influence of the inspection rate on the system output as well. According to Figure 5-8, the fluctuation of the mean values during the replications is significantly higher when the sample rate is in the order of 20% of the subset size or less. For values over 30%, the variation decreases consistently; however, the additional benefit does grow up in proportion to the additional measurement effort. The situation is not so clear in Figure 5-9, where the only distinguishable difference happens when the inspection rate is set to 5%. Here the magnitudes are in order of a fiftieth of the standard deviation values.

Table 5-11. St. Dev. of the Mean Values of the Resulting Assemblies' Length

Exp.	Inspection Rate (%)									
	5%	10%	20%	30%	40%	50%	60%	70%	80%	90%
1	0.0269	0.0175	0.0139	0.0104	0.0083	0.0072	0.0067	0.0069	0.0054	0.0053
2	0.0356	0.0184	0.0144	0.0141	0.0096	0.0081	0.0076	0.0067	0.0057	0.0060
3	0.0260	0.0163	0.0141	0.0115	0.0089	0.0084	0.0076	0.0068	0.0058	0.0051
4	0.0337	0.0181	0.0144	0.0127	0.0098	0.0075	0.0079	0.0074	0.0061	0.0057
5	0.0261	0.0190	0.0124	0.0099	0.0089	0.0078	0.0061	0.0062	0.0053	0.0049
6	0.0323	0.0187	0.0158	0.0146	0.0110	0.0104	0.0096	0.0076	0.0074	0.0061
7	0.0267	0.0195	0.0126	0.0123	0.0097	0.0077	0.0073	0.0063	0.0056	0.0055
8	0.0342	0.0194	0.0117	0.0112	0.0103	0.0125	0.0093	0.0084	0.0073	0.0054

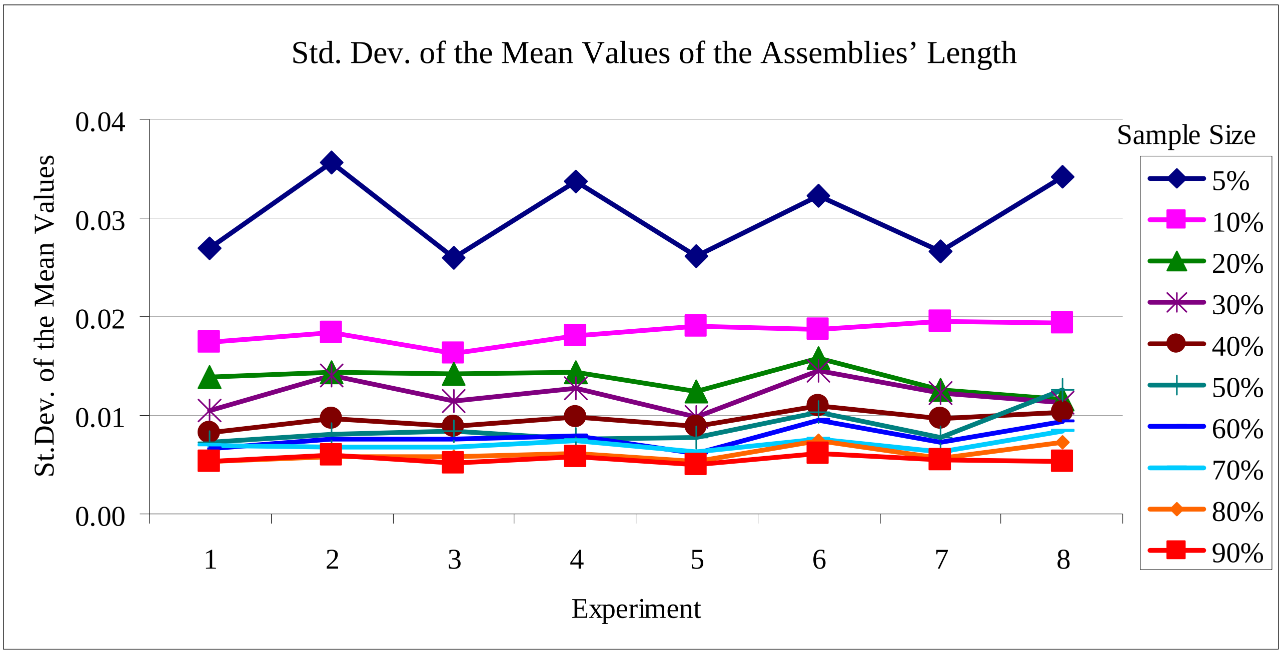


Figure 5-8. Standard deviation of the mean values of the resulting assemblies' length.

Table 5-12. St. Dev. of the Standard Deviation Values of the Resulting Assemblies' Length

Exp.	Inspection Rate (%)									
	5%	10%	20%	30%	40%	50%	60%	70%	80%	90%
1	0.0067	0.0055	0.0052	0.0053	0.0047	0.0051	0.0054	0.0049	0.0056	0.0056
2	0.0074	0.0055	0.0049	0.0050	0.0053	0.0056	0.0047	0.0050	0.0050	0.0049
3	0.0071	0.0050	0.0049	0.0046	0.0051	0.0051	0.0046	0.0048	0.0045	0.0049
4	0.0072	0.0063	0.0051	0.0044	0.0048	0.0049	0.0048	0.0050	0.0051	0.0055
5	0.0070	0.0056	0.0050	0.0055	0.0052	0.0054	0.0044	0.0053	0.0048	0.0056
6	0.0079	0.0053	0.0050	0.0055	0.0048	0.0048	0.0057	0.0049	0.0051	0.0053
7	0.0075	0.0056	0.0056	0.0048	0.0055	0.0051	0.0046	0.0047	0.0049	0.0049
8	0.0070	0.0057	0.0050	0.0049	0.0050	0.0051	0.0055	0.0053	0.0048	0.0044

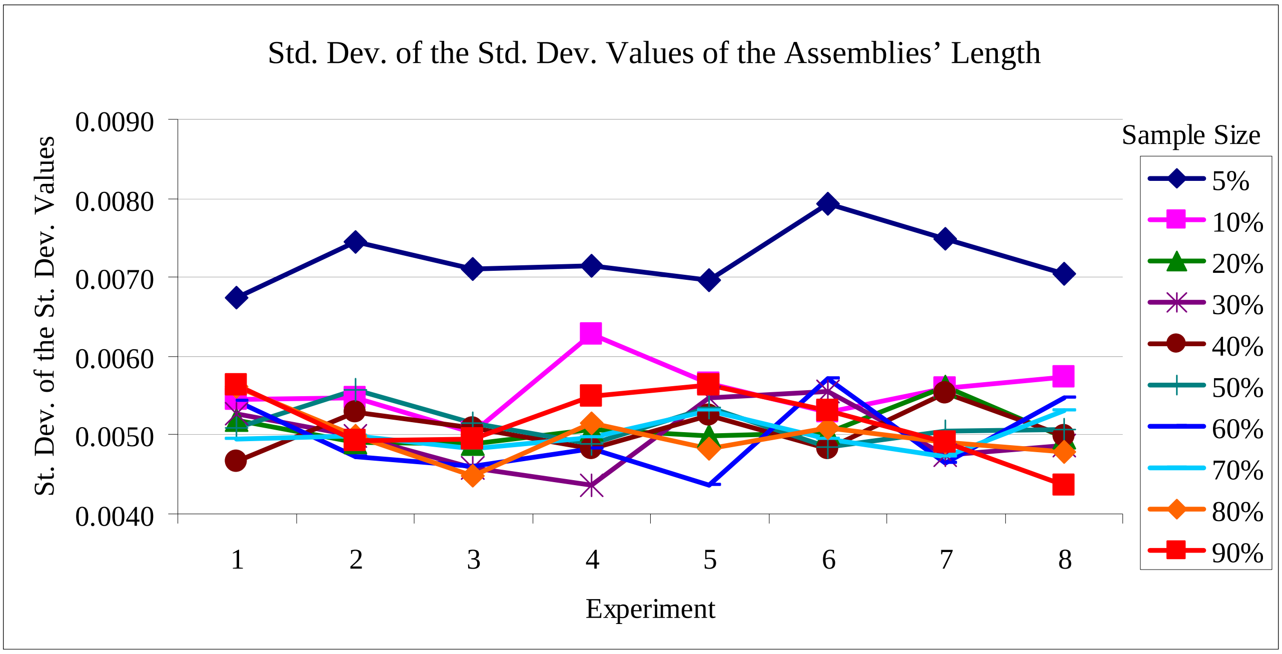


Figure 5-9. Std. Dev. of the standard deviation values of the resulting assemblies' length.

5.3.3. Tendency Measure Estimators

The purpose of these experiments is to quantify the influence of the estimator used as the central tendency measure on the effectiveness of the proposed SFFCM-based assembling technique [Her12-2]. In this case, while the inspection rate remained fixed at 20%, the subset size was set to 100, 125, 200, 250 and 500. This time, for each value of the subset size, the simulation of the experiments in Table 5-13 was replicated 700 times.

Table 5-13. Design of Experiments

Exp.	Random Sampling		Subset Pattern		Tendency Measure Estimator	
	Simple	Systematic	Common	Individual	$\bar{x}_{1,sub}$	$\bar{x}_{1,sub,cdna}$
1	√		√		√	
2	√		√			√
3	√			√	√	
4	√			√		√
5		√	√		√	
6		√	√			√
7		√		√	√	
8		√		√		√

In this stage of the research the focus is set on the quest for an estimator of the central tendency that helps optimize the number of adjustments executed by the controller during the production cycle. Thereby, in these experiments it was necessary to vary the subset size. For more clarity, setting the subset size to 100 will result in 10 adjustments if the lot is of 1,000 items. In the same way, a 500-item subset will demand 2 adjustments per lot.

Since SFFCM adjusts the components' specifications in response to the evolution of the detected long-term drift, modeling properly the drift is crucial to achieve a good performance of the controller. It is in this point where the dilemma of using the sample mean or another estimator arises.

Commonly, classical and modern approaches do not even conceive the idea of evaluating alternatives to replace the traditional sample mean by a different estimator [Man61, Zoc11]. The quality of the sample mean as estimator of the mean for a given subset is not under discussion; however, for the benefit of the system output it is more convenient to have a full picture of the long-term drift over time rather than a small and partial picture that only capture the central tendency in one subset.

The fundamental difference between the sample mean and the proposed cumulative de-noised average strives in that the first is computed using only the data retrieved from the last inspected subset, while the second one "possesses memory" and takes into account the data gathered from some of the previous inspected subsets of a given lot.

Table 5-14 and Table 5-15 show that, in spite of the sampling strategy, the system output is sensitive to the application of the cumulative de-noised average $\bar{x}_{1,sub(i),cdna}$ as a substitute of the sample mean $\bar{x}_{1,sub(i)}$. As seen in Figure 5-10 and Figure 5-11, experiments 2, 4, 6 and 8 systematically produced lower mean shift and lower standard deviation. This situation is particularly notorious when the subset size is either 100 or 125, which implies 10 or 8 adjustments per lot, respectively.

Table 5-14. Average Mean of the Resulting Assemblies' Length

Adjustments (Subset Size)	Experiment 1	2	3	4	5	6	7	8
2 (500)	29.9489	29.9470	29.9481	29.9468	29.9490	29.9458	29.9484	29.9464
4 (250)	29.9494	29.9511	29.9489	29.9518	29.9487	29.9511	29.9501	29.9513
5 (200)	29.9480	29.9511	29.9473	29.9506	29.9498	29.9499	29.9481	29.9499
8 (125)	29.9485	29.9555	29.9484	29.9546	29.9493	29.9543	29.9499	29.9564
10 (100)	29.9491	29.9522	29.9490	29.9509	29.9493	29.9529	29.9487	29.9516

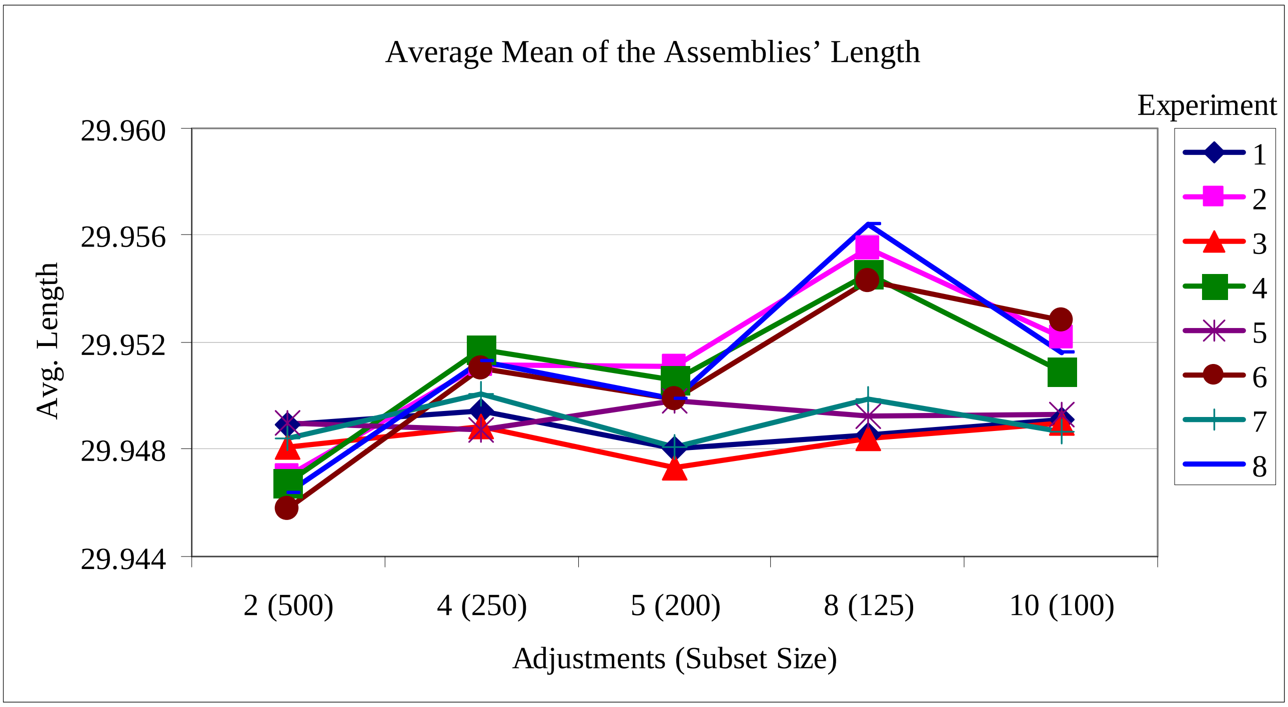


Figure 5-10. Average sample mean of the resulting assemblies' length.

Table 5-15. Average Std. Dev. of the Resulting Assemblies' Length

Adjustments	Experiment							
(Subset Size)	1	2	3	4	5	6	7	8
2 (500)	0.2494	0.2495	0.2496	0.2495	0.2494	0.2492	0.2491	0.2494
4 (250)	0.2486	0.2480	0.2478	0.2478	0.2478	0.2481	0.2478	0.2477
5 (200)	0.2474	0.2473	0.2473	0.2479	0.2472	0.2474	0.2468	0.2475
8 (125)	0.2449	0.2457	0.2453	0.2454	0.2455	0.2463	0.2452	0.2459
10 (100)	0.2456	0.2457	0.2454	0.2462	0.2455	0.2462	0.2454	0.2458

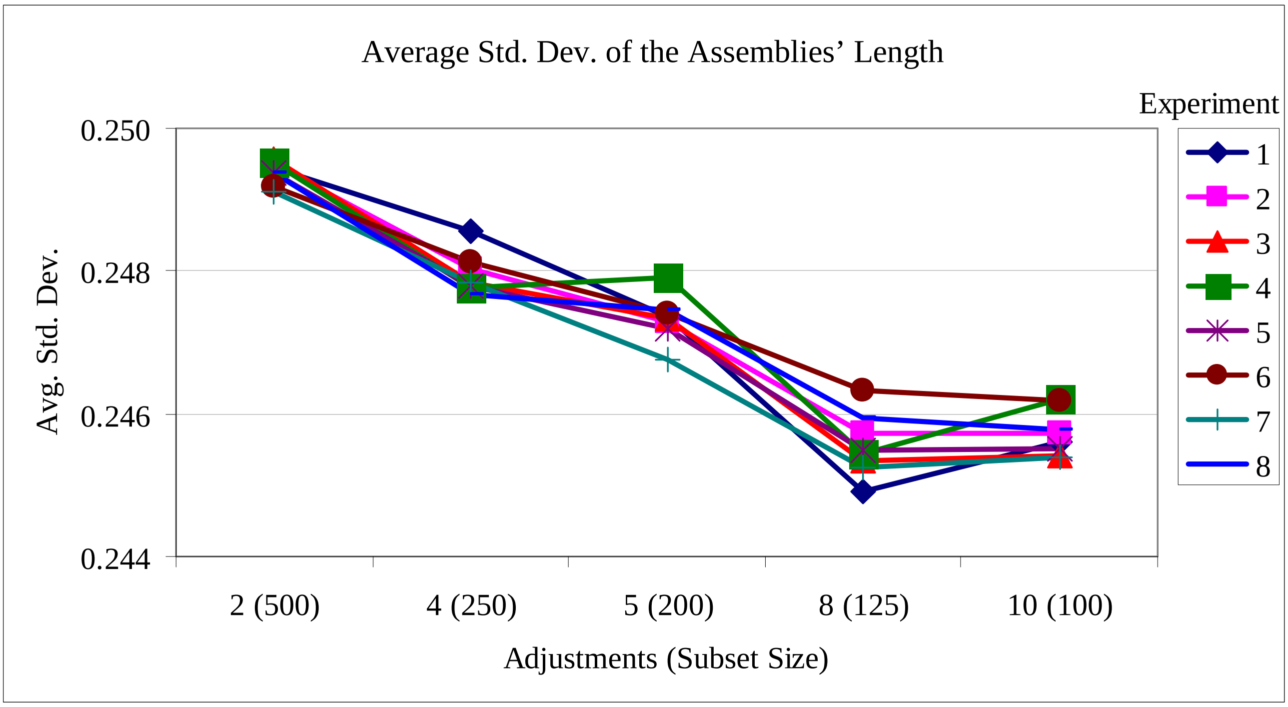


Figure 5-11. Average standard deviation of the resulting assemblies' length.

A priori, these experiments demonstrate that, if the cumulative de-noised average is used, only 8 adjustments are enough to deliver reasonably good results. Figure 5-12, however, shows a light tendency to increase the fluctuation of the mean values during the replications as the subset size decreases. These are not necessarily bad news because the differences are in the order of few thousandths of the expected mean.

Figure 5-13 shows also an increment in the variation of the standard deviation during the replications. In special, when the proposed cumulative de-noised average is applied instead of the sample mean. The fluctuation, in the order of the fiftieth of the expected standard deviation, is not concerning when it is compared to the benefit achieved. In this case, the average mean shift decreased by 90%, from 0.45 to 0.05 and the average standard deviation decreased by 15%, from 0.29 to 0.26 in the best case.

Table 5-16. St. Dev. of the Mean Values of the Resulting Assemblies' Length

Adjustments	Experiment							
(Subset Size)	1	2	3	4	5	6	7	8
2 (500)	0.0134	0.0136	0.0143	0.0136	0.0131	0.0137	0.0128	0.0137
4 (250)	0.0135	0.0138	0.0135	0.0147	0.0130	0.0146	0.0128	0.0142
5 (200)	0.0137	0.0151	0.0134	0.0151	0.0126	0.0154	0.0130	0.0145
8 (125)	0.0132	0.0157	0.0130	0.0143	0.0134	0.0149	0.0128	0.0153
10 (100)	0.0132	0.0151	0.0130	0.0152	0.0131	0.0146	0.0130	0.0145

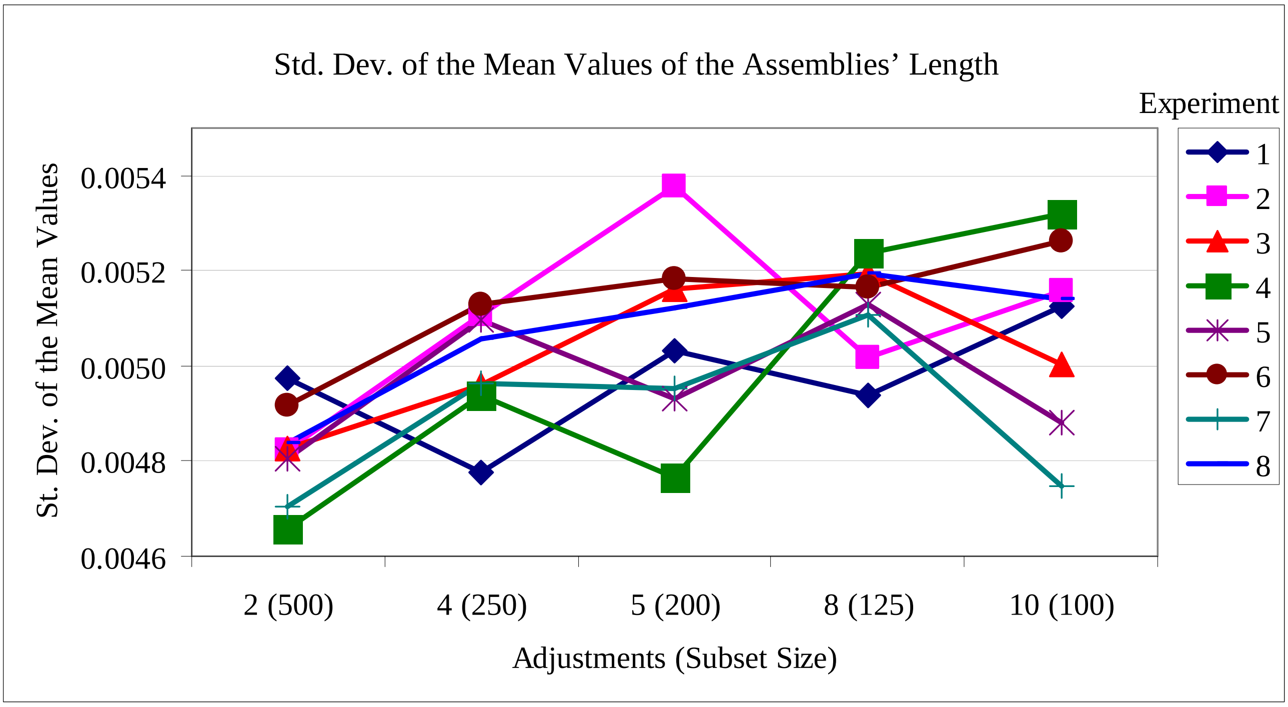


Figure 5-12. Standard deviation of the mean values of the resulting assemblies' length.

Table 5-17. St. Dev. of the Standard Deviation Values of the Resulting Assemblies' Length

Adjustments	Experiment							
(Subset Size)	1	2	3	4	5	6	7	8
2 (500)	0.0050	0.0048	0.0048	0.0047	0.0048	0.0049	0.0047	0.0048
4 (250)	0.0048	0.0051	0.0050	0.0049	0.0051	0.0051	0.0050	0.0051
5 (200)	0.0050	0.0054	0.0052	0.0048	0.0049	0.0052	0.0050	0.0051
8 (125)	0.0049	0.0050	0.0052	0.0052	0.0051	0.0052	0.0051	0.0052
10 (100)	0.0051	0.0052	0.0050	0.0053	0.0049	0.0053	0.0047	0.0051

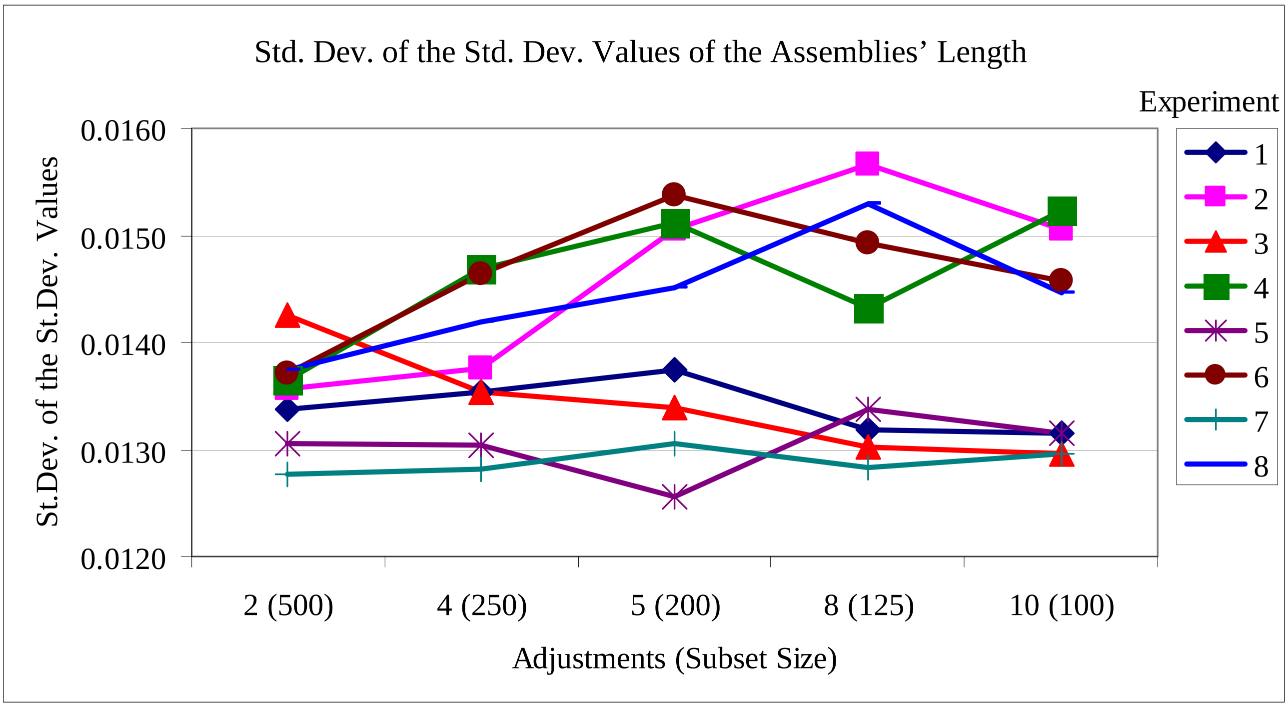


Figure 5-13. Std. Dev. of the standard deviation values of the resulting assemblies' length.

Figure 5-14 and Figure 5-15 show the difference between applying the sample mean and the cumulative de-noise average when modeling a detectable long-time drift.

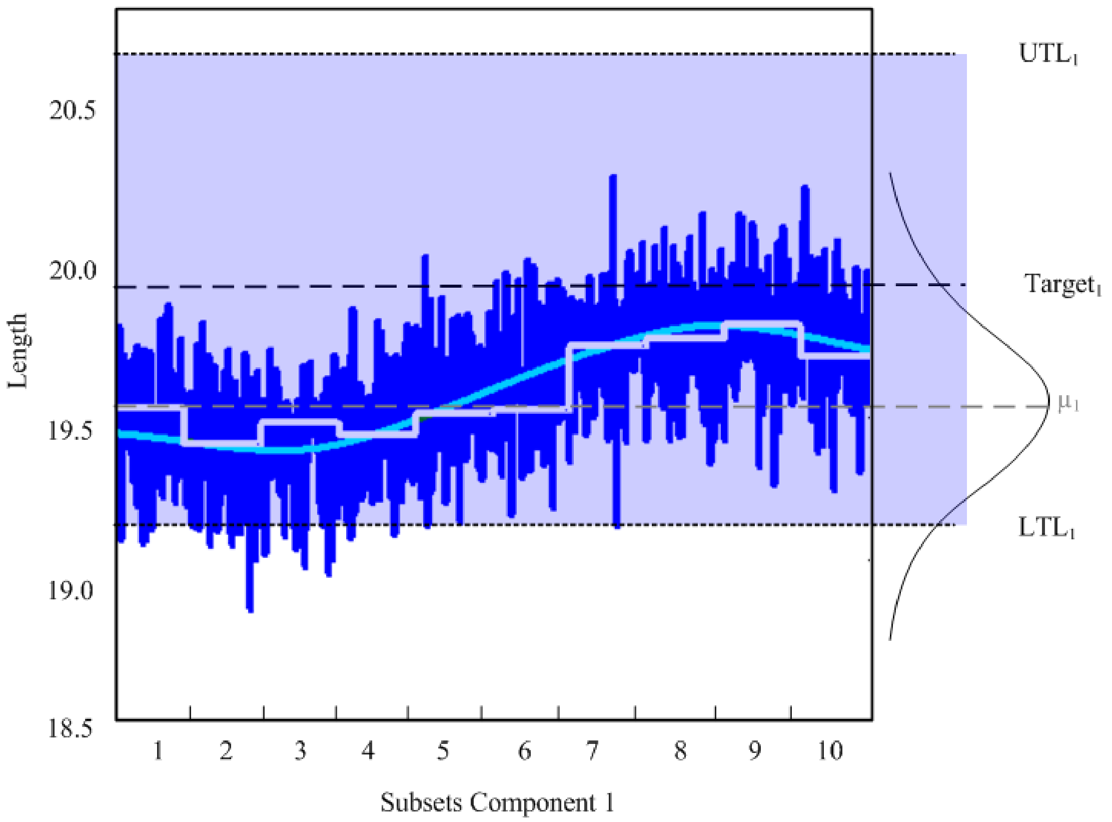


Figure 5-14. Long-term drift modeling by applying the sample mean.

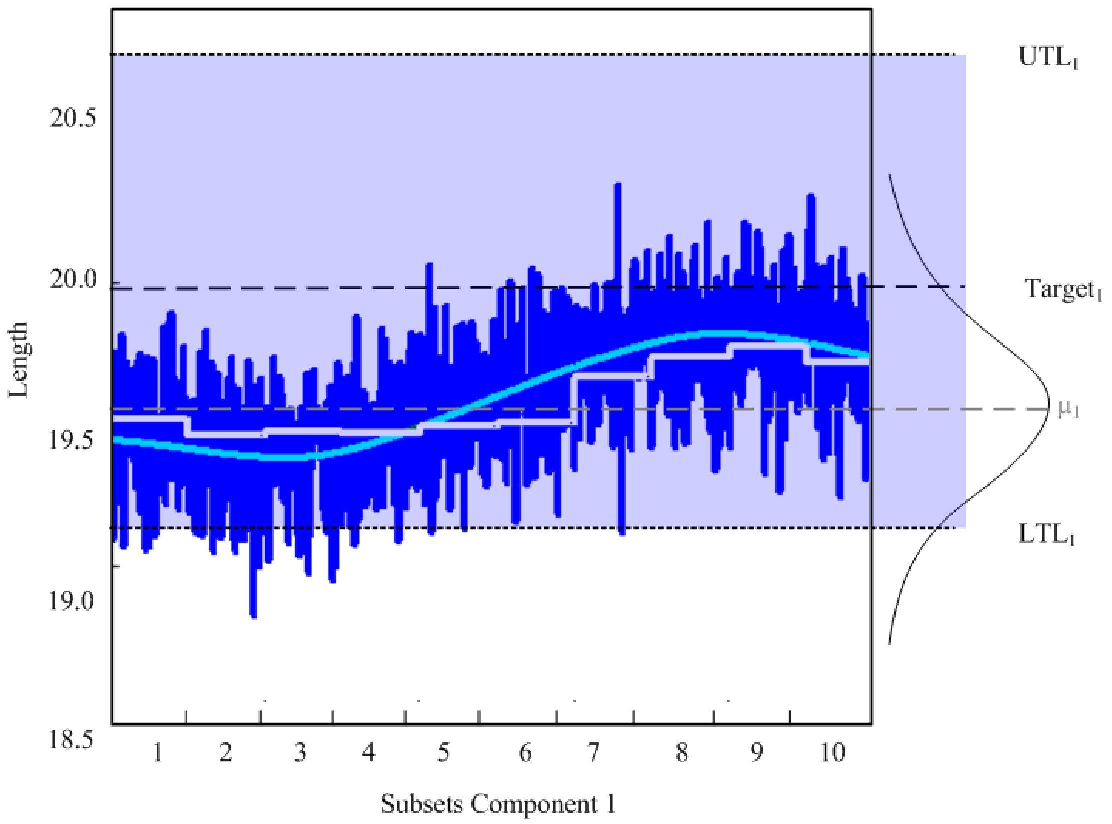


Figure 5-15. Long-term drift modeling by applying the cumulative de-noised average.

Since the sample mean "lacks of memory", it is not rare to see big jumps between the estimated values in consecutive subsets. On the contrary, the cumulative de-noised average prevents such jumps by means of taking into account the data gathered in the previous subsets.

Having an estimator "with memory" that takes into account the available data proved to be a good alternative because it made possible to reduce the number of adjustments, and therefore to spare resources, without sacrificing precision in the system output.

A different perspective to visualize the results of these experiments is provided by the process capability indices c_p and c_{pk}. Table 5-18 and Table 5-19 summarize these data.

Figure 5-16 shows an evident improvement of the potential capability index as the subset size approaches to 125, which is the inflexion point. Unfortunately, not much can be said about the influence of the central tendency estimator here. However, Figure 5-17 makes possible to distinguish this influence. There, experiments 2, 4 and 8 present peak values when the subset size is set to 125. Experiment 6 does not exhibit such peak at 125 but it is still better than the experiments in which the sample mean was used.

Table 5-18. Average Potential Capability Index c_p

Adjustments	Experiment							
(Subset Size)	1	2	3	4	5	6	7	8
2 (500)	1.3363	1.3361	1.3356	1.3359	1.3367	1.3377	1.3380	1.3366
4 (250)	1.3411	1.3440	1.3449	1.3454	1.3452	1.3434	1.3449	1.3459
5 (200)	1.3476	1.3479	1.3476	1.3445	1.3485	1.3472	1.3508	1.3471
8 (125)	1.3610	1.3565	1.3587	1.3582	1.3578	1.3532	1.3592	1.3554
10 (100)	1.3572	1.3565	1.3583	1.3539	1.3577	1.3540	1.3583	1.3562

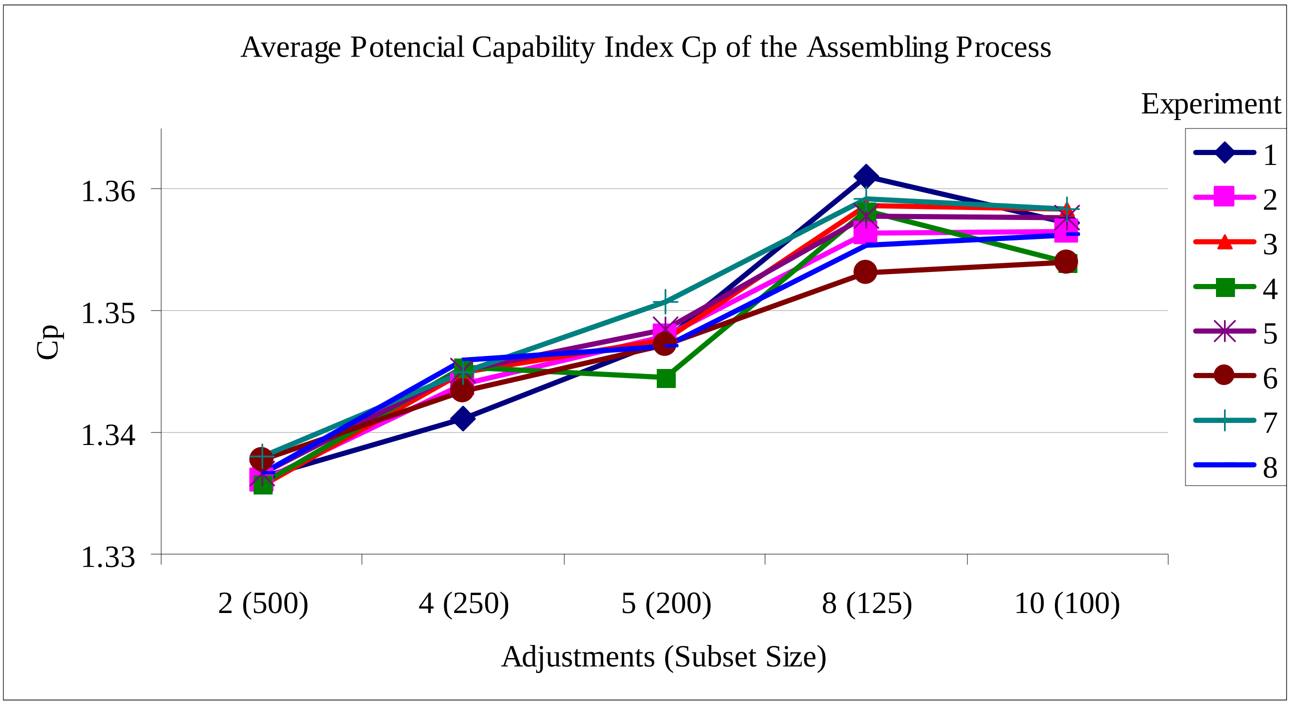


Figure 5-16. Average potential capability index c_p.

Table 5-19. Average Actual Capability Index c_{pk}

Adjustments	Experiment							
(Subset Size)	1	2	3	4	5	6	7	8
2 (500)	1.2680	1.2653	1.2663	1.2647	1.2685	1.2652	1.2690	1.2649
4 (250)	1.2732	1.2783	1.2761	1.2805	1.2762	1.2776	1.2778	1.2804
5 (200)	1.2776	1.2820	1.2766	1.2781	1.2809	1.2797	1.2807	1.2796
8 (125)	1.2910	1.2961	1.2886	1.2965	1.2890	1.2913	1.2911	1.2963
10 (100)	1.2882	1.2916	1.2890	1.2875	1.2889	1.2901	1.2887	1.2906

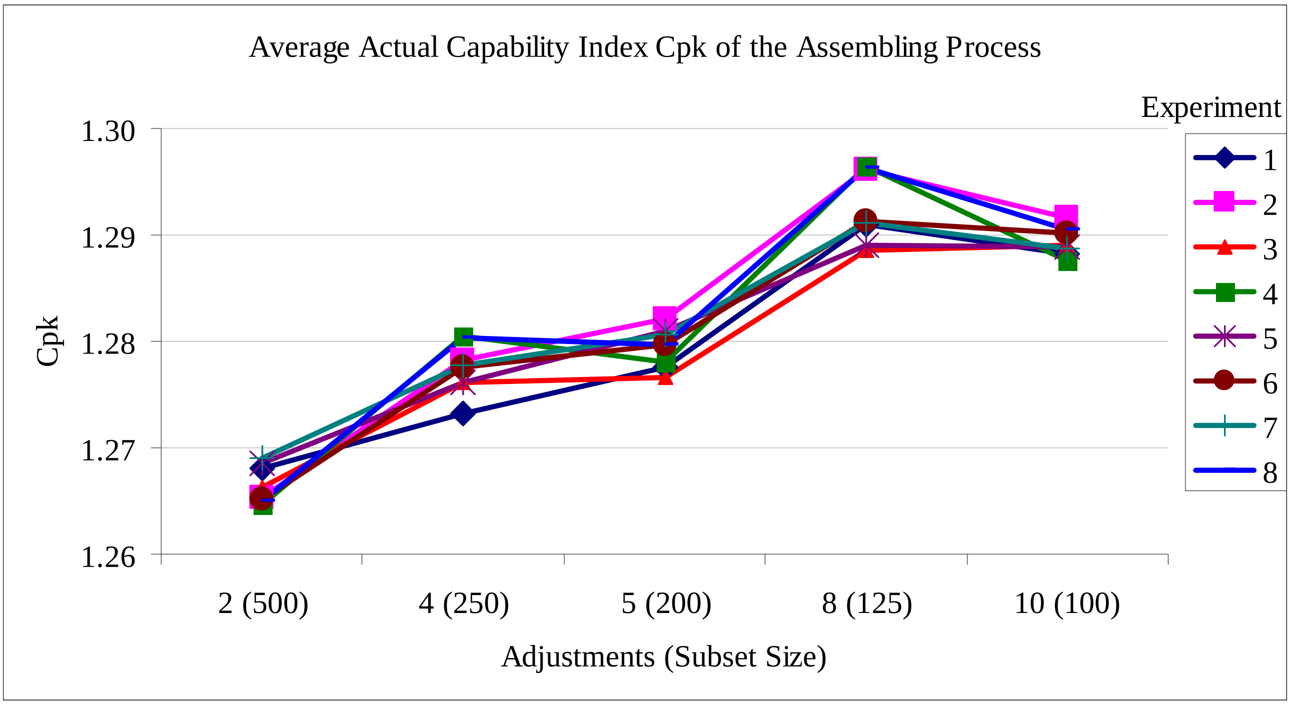


Figure 5-17. Average actual capability index c_{pk}.

5.3.4. Measurement Uncertainty

The purpose of these experiments is to quantify the influence of the uncertainty associated to the measurements on the effectiveness of the proposed SFFCM-based assembling technique. In this case, the subset size remained fixed at 100, whereas the inspection rate was set to 20%, 30%, 40% and 50%.

Different from previous simulations, in this opportunity the experiments address the problem of determining the right adjustments in the presence of different levels of measurement uncertainty. Table 5-20 summarizes the values of the sample mean $\bar{x}_{1,sub(i)}$ and sample standard deviation $s_{1,sub(i)}$ obtained for the subsets of the lot of Component 1 when the inspection rates or sample size was set to different levels. The importance of these data resides in their direct influence in the adjustments to the matching subsets of Component 2.

Table 5-20. Sample Mean $\bar{x}_{1,sub(i)}$ and Sample Standard Deviation $s_{1,sub(i)}$

Sub set	Inspection Rate							
	20 %		30 %		40 %		50 %	
	$\bar{x}_{1,sub(i)}$	$s_{1,sub(i)}$	$\bar{x}_{1,sub(i)}$	$s_{1,sub(i)}$	$\bar{x}_{1,sub(i)}$	$s_{1,sub(i)}$	$\bar{x}_{1,sub(i)}$	$s_{1,sub(i)}$
1	19.43	0.19	19.41	0.19	19.45	0.18	19.41	0.19
2	19.40	0.19	19.40	0.19	19.38	0.19	19.37	0.19
3	19.44	0.18	19.39	0.18	19.46	0.19	19.37	0.19
4	19.51	0.19	19.54	0.19	19.51	0.19	19.50	0.19
5	19.59	0.19	19.59	0.18	19.63	0.20	19.55	0.19
6	19.70	0.18	19.69	0.18	19.72	0.20	19.70	0.19
7	19.79	0.20	19.80	0.19	19.81	0.19	19.78	0.19
8	19.76	0.19	19.80	0.18	19.80	0.19	19.83	0.19
9	19.79	0.19	19.83	0.19	19.80	0.19	19.84	0.19
10	19.75	0.19	19.71	0.18	19.76	0.19	19.67	0.19

The target of the matching subsets of Component 2 can be computed directly with the following formulae:

$$\hat{L}_{2,adj,sub(i)} = L_{assy} - \bar{x}_{1,sub(i)} \quad (5\text{-}4)$$

As explained in Chapter 3, the computation of the subset tolerances is not trivial because the measurement uncertainty has to be considered this time.

$$\hat{t}_{1,sub(i),unc} = \hat{t}_{1,sub(i)} + u \tag{5-5}$$

If $\Delta t_{1,sub(i)}$ defines the difference between the nominal tolerance t_1 and half of the band of $6s_{1,sub(i)}$ where 99.73% of the items' length are expected to fall and u is the measurement uncertainty, the relation between $\Delta t_{1,sub(i)}$ and u can expressed by means of the ratio in equation (5-7).

$$\Delta t_{1,sub(i)} = t_1 - 3s_{1,sub(i)} \tag{5-6}$$

$$X\% = \frac{u}{\Delta t_{1,sub(i)}} \tag{5-7}$$

To avoid an analysis in terms u equation 5-5 can be rewritten in terms of the variable ratio $u/\Delta t_{1,sub(i)}$ as follows:

$$\hat{t}_{1,sub(i),unc} = \hat{t}_{1,sub(i)} + (X\%)\Delta t_{1,sub(i)} \tag{5-8}$$

$$\hat{t}_{1,sub(i),unc} = 3s_{1,sub(i)} + (X\%)(t_1 - 3s_{1,sub(i)}) \tag{5-9}$$

Thus, the adjusted tolerance of the matching subsets of Component 2 can be computed using the following estimator:

$$\hat{t}_{2,adj,sub(i),unc} = \sqrt{t_{assy}^2 - \hat{t}_{1,sub(i),unc}^2} \tag{5-10}$$

Even though the formulae above were already presented in Chapter 3, it was worthwhile to recall them again because the reasoning to derive and understand these equations is not intuitive.

Table 5-21 summarizes the simulation results obtained for the adjusted target $L_{2,adj,sub(i)}$ and tolerance $t_{2,adj,sub(i)}$ when the inspection rate was set to 30% and a subset size to 100.

Table 5-21. Adjusted Specifications $L_{2,adj,sub(i)}$ and $t_{2,adj,sub(i)}$

Subset	$\bar{x}_{1,sub(i)}$	$s_{1,sub(i)}$	$t_{1,sub(i)}$	$L_{2,adj,sub(i)}$	$t_{2,adj,sub(i)}$	$c_{p,2,adj,sub(i)}$
1	19.41	0.19	0.57	10.59	0.82	1.83
2	19.40	0.19	0.57	10.60	0.82	1.83
3	19.39	0.18	0.54	10.61	0.84	1.87
4	19.54	0.19	0.57	10.46	0.82	1.83
5	19.59	0.18	0.54	10.41	0.84	1.87
6	19.69	0.18	0.54	10.31	0.84	1.87
7	19.80	0.19	0.57	10.20	0.82	1.83
8	19.80	0.18	0.54	10.20	0.84	1.87
9	19.83	0.19	0.57	10.17	0.82	1.83
10	19.71	0.18	0.54	10.29	0.84	1.87

The inclusion of the measurement uncertainty in the analysis has a significant influence in the adjusted tolerance $t_{2,adj,sub(i),unc}$ and, consequently, in the capability index $c_{p,2,adj,sub(i),unc}$. Table 5-22 summarizes the result of applying different ratios $u/\Delta t_{1,sub(1)}$ in the subset 1 of Component 1 to calculate $t_{2,adj,sub(1),unc}$.

Table 5-22. Adjusted Tolerance $t_{2,adj,sub(1),unc}$ and $c_{p,2,adj,sub(1),unc}$ for Different Ratios $u/\Delta t_{1,sub(1)}$

$u/\Delta_{1,sub(i)}$	X%	$\bar{x}_{1,sub(1)}$	$s_{1,sub(1)}$	$\Delta t_{1,sub(1)}$	$t_{1,sub(1),unc}$	$t_{2,adj,sub(1),unc}$	$c_{p,2,adj,sub(1),unc}$
0	0	0.19	0.57	0.25	0.58	0.82	1.83
0.1	10	0.19	0.57	0.25	0.60	0.80	1.79
0.2	20	0.19	0.57	0.25	0.62	0.78	1.74
0.3	30	0.19	0.57	0.25	0.65	0.76	1.70
0.4	40	0.19	0.57	0.25	0.67	0.74	1.65
0.5	50	0.19	0.57	0.25	0.70	0.72	1.60
0.6	60	0.19	0.57	0.25	0.72	0.69	1.54
0.7	70	0.19	0.57	0.25	0.75	0.67	1.48
0.8	80	0.19	0.57	0.25	0.77	0.64	1.42
0.9	90	0.19	0.57	0.25	0.80	0.61	1.35
1	100	0.19	0.57	0.25	0.82	0.58	1.27

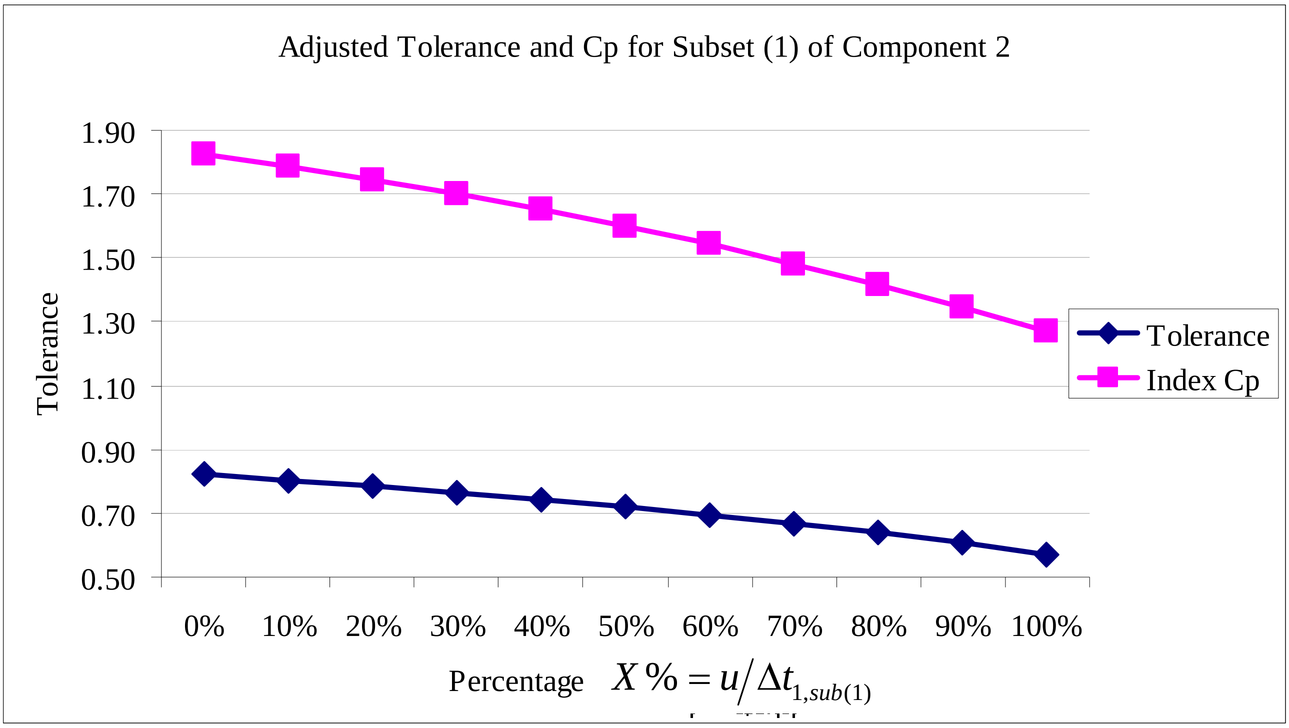


Figure 5-18. Adjusted tolerance $t_{2,adj,sub(i),unc}$ and $c_{p,2,adj,sub(i)}$ for different ratios $u/\Delta t_{1,sub(1)}$.

The influence of the measurement uncertainty u in the computation of $t_{2,adj,sub(i),unc}$ and $c_{p,2,adj,sub(i)}$ is evident in Figure 5-18. Since in the subset 1 of Component 1, the value of $\Delta t_{1,sub(1)}$ is constant (equation 5-6), the ratio $u/\Delta t_{1,sub(1)}$ is affected only by the value of u.

Simulation results show that both the adjusted tolerance of the matching subset of Component 2 and the corresponding capability index decrease as the magnitude of the measurement uncertainty u increases. Therefore, the highest value of the adjusted tolerance $t_{2,adj,sub(i),unc}$ is obtained when u approaches to zero. In this situation, $t_{2,adj,sub(i),unc}$ increases by 42% with respect to the nominal value t_2 from 0.58 to 0.82.

In practice, the measurement uncertainty that is added to $t_{1,sub(i)}$ to determine $t_{1,sub(i),unc}$,and thus, to compute the adjusted $t_{2,adj,sub(i),unc}$, will impact directly the number of items of Component 2 that fall out of their respective tolerance range and which, in consequence, can be considered as defective units or scrap. These numbers are summarized in Table 5-23, where each entry represents the average of 500 replications. In this simulation, the inspection rate was kept at 30%; whereas the subset size at 100.

Table 5-23. Average Number of Units out of Tolerance – Component 2

$X\% = \dfrac{u}{\Delta_{1,sub(i)}}$	Units out of Tolerance
	Component 2
0 %	26.6
10 %	28.3
20 %	33.0
30 %	35.3
40 %	43.3
50 %	50.4
60 %	60.9
70 %	74.1
80 %	97.0
90 %	125.9
100 %	164.7

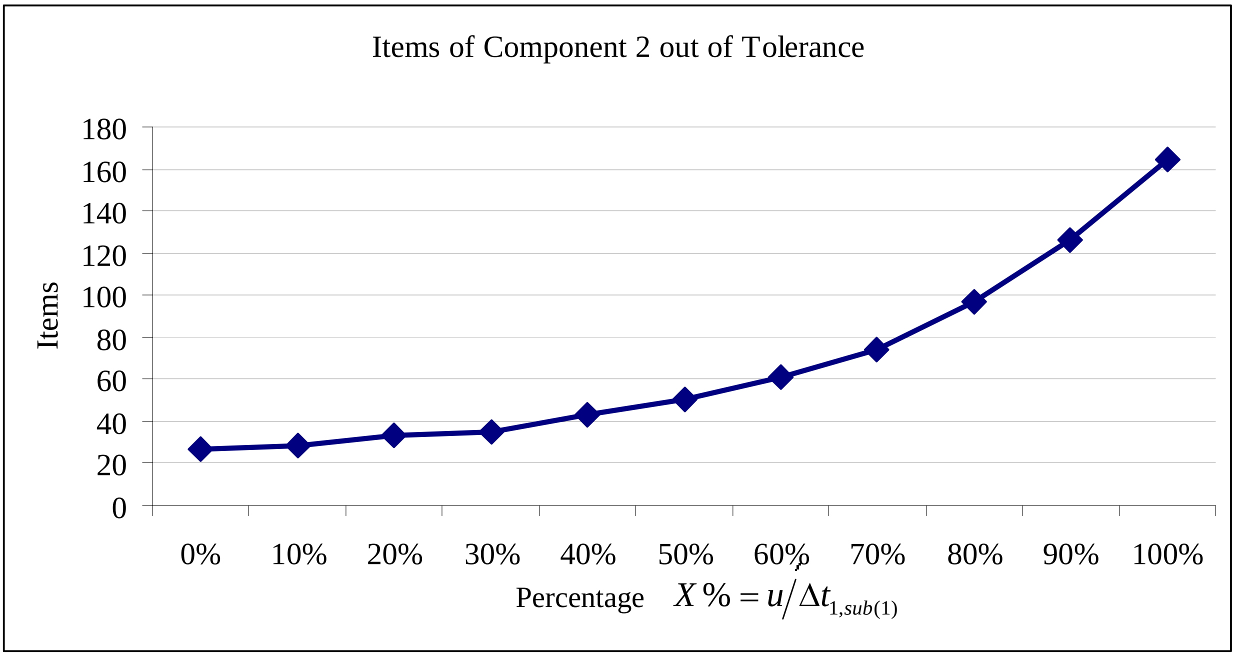


Figure 5-19. Average number of items of Component 2 out of tolerance.

The presence of such amount of “defective” items does not mean that all of them have to be rejected. SFFCM was conceived having in mind the presence of high dimensional variation so that these component items are accommodated in such a way that the resulting lot of assemblies have minimized mean shift and a reduced standard deviation.

5.3.5. Response Delay

The purpose of these experiments is to quantify the influence of response delays in the application of the adjustments in the effectiveness of the proposed SFFCM-based assembling technique [Her13-1]. In this case, while the inspection rate remained fixed at 20% and the subset size fixed at 125 (i.e. 8 adjustments), the magnitude if the response delays was set to 0%, 10%, 20%, 30%, 40%, 50%, 75% and 100%.

Response delays equal to 0% imply the absence of delay at all. On the contrary, delays equal to 100% imply an offset equivalent to one subset. For each value of the subset size, the simulation of the experiments in Table 5-24 was replicated 700 times.

Since the implementation of an adjustment on a running process involves many considerations like the machines' setup or the conveyors' speed, it is necessary to define meaningful measure to express the response delays existing between the point in which an adjustment is triggered and moment in which it really produces the desired effect. In this research response delays are directly linked and expressed in terms of the number of items that are transported by the conveyors during the delay lapse and that are not affected by the adjustment in progress. Thus, independently from the conveyor speed, response delays can be always characterized by the number of items that passed by without being caught in time. It is assumed that the conveyors' speed is constant and that the items pass in front of the measurement sensors at fixed intervals of time. The definition of the experiments simulated in this stage of the research is presented in Table 5-24.

Table 5-24. Design of Experiments for Response Delays

Exp.	Random Sampling		Subset Pattern		Tendency Measure Estimator	
	Simple	Systematic	Common.	Individual	$\overline{x}_{1,sub}$	$\overline{x}_{1,sub,cdna}$
1	√		√		√	
2	√		√			√
3	√			√	√	
4	√			√		√
5		√	√		√	
6		√	√			√
7		√		√	√	
8		√		√		√

Table 5-25 and Table 5-26 summarize the simulation results. In this case, the system output is affected in proportion to the magnitude of the response delays. This is shown in Figure 5-20 and Figure 5-21 where both the average mean shift and the average standard deviation grow up as the response delay increases. Similar behavior is observed in all the experiments.

Table 5-25. Average Mean of the Assemblies' Length

Exp.	Response Delay							
	0%	10%	20%	30%	40%	50%	75%	100%
1	29.9485	29.9462	29.9439	29.9404	29.9378	29.9343	29.9266	29.9189
2	29.9555	29.9529	29.9506	29.9480	29.9432	29.9413	29.9344	29.9266
3	29.9484	29.9463	29.9443	29.9406	29.9375	29.9345	29.9273	29.9183
4	29.9546	29.9530	29.9514	29.9468	29.9439	29.9418	29.9334	29.9266
5	29.9493	29.9456	29.9439	29.9415	29.9375	29.9346	29.9264	29.9200
6	29.9543	29.9532	29.9495	29.9460	29.9434	29.9408	29.9327	29.9265
7	29.9499	29.9458	29.9431	29.9399	29.9373	29.9339	29.9265	29.9190
8	29.9564	29.9528	29.9513	29.9480	29.9442	29.9402	29.9324	29.9262

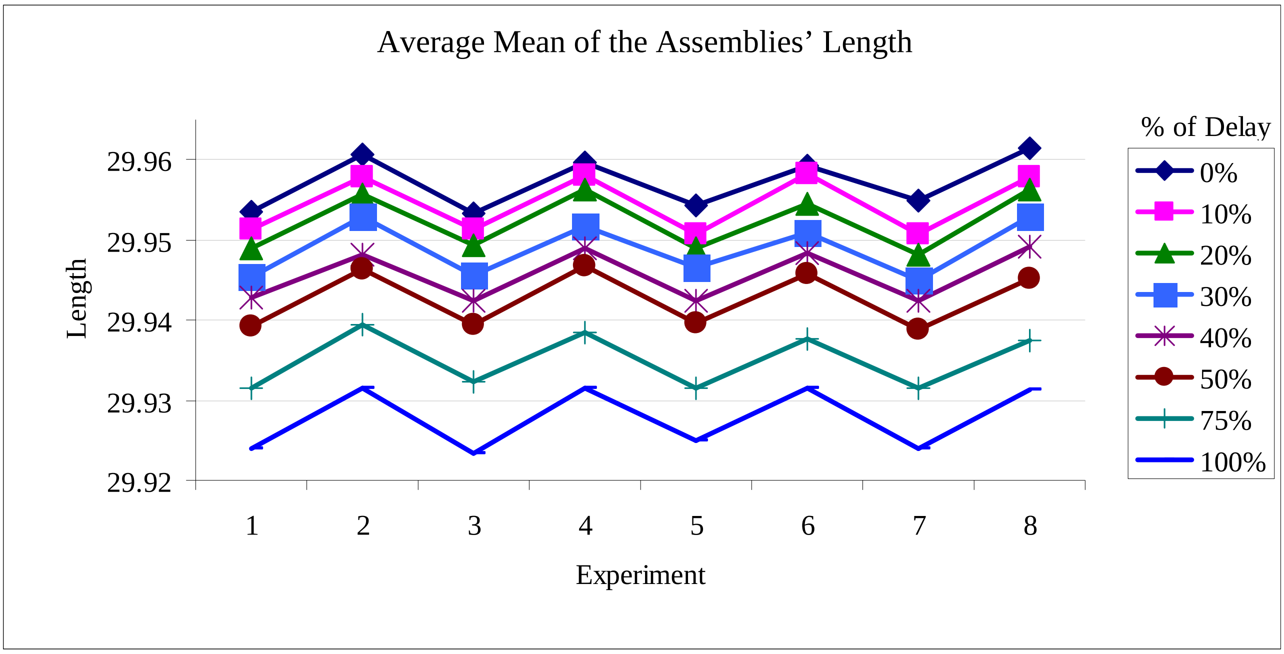


Figure 5-20. Average mean of the resulting assemblies' length.

Table 5-26. Average Std. Dev. of the Assemblies' Length

Exp.	Response Delay							
	0%	10%	20%	30%	40%	50%	75%	100%
1	0.2449	0.2518	0.2587	0.2662	0.2742	0.2826	0.3019	0.3233
2	0.2457	0.2527	0.2602	0.2688	0.2760	0.2852	0.3060	0.3270
3	0.2453	0.2517	0.2587	0.2665	0.2741	0.2820	0.3018	0.3228
4	0.2454	0.2527	0.2603	0.2687	0.2764	0.2853	0.3052	0.3274
5	0.2455	0.2516	0.2589	0.2667	0.2744	0.2825	0.3016	0.3236
6	0.2463	0.2531	0.2603	0.2690	0.2763	0.2851	0.3053	0.3274
7	0.2452	0.2519	0.2587	0.2665	0.2741	0.2822	0.3021	0.3231
8	0.2459	0.2528	0.2599	0.2687	0.2763	0.2845	0.3051	0.3271

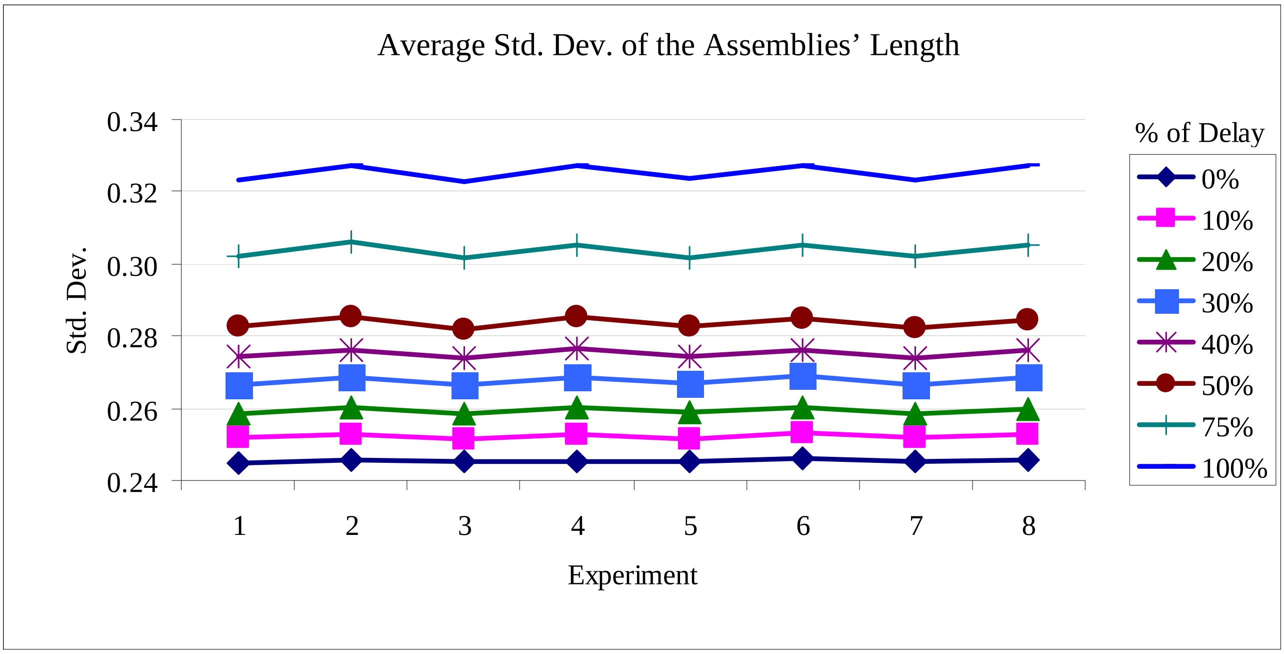


Figure 5-21. Average standard deviation of the resulting assemblies' length.

A quick look at the variation of the mean values, Table 5-27, reveals that the fluctuation of the values responds to the experiment setup. However, Table 5-28 and Figure 5-23 show that the fluctuation of the standard deviation values is, indeed, sensitive to the magnitude of the response delays. Thereby, the fluctuation of the standard deviation found during the replications grows as response delays increase.

Table 5-27. St. Dev. of the Mean Values of the Assemblies' Length

Exp.	Response Delay							
	0%	10%	20%	30%	40%	50%	75%	100%
1	0.0132	0.0128	0.0130	0.0125	0.0122	0.0120	0.0123	0.0120
2	0.0157	0.0153	0.0152	0.0145	0.0144	0.0145	0.0149	0.0144
3	0.0130	0.0128	0.0131	0.0127	0.0133	0.0121	0.0130	0.0129
4	0.0143	0.0148	0.0148	0.0156	0.0153	0.0148	0.0148	0.0140
5	0.0134	0.0126	0.0132	0.0125	0.0122	0.0124	0.0122	0.0125
6	0.0149	0.0151	0.0147	0.0140	0.0151	0.0140	0.0141	0.0151
7	0.0128	0.0131	0.0127	0.0126	0.0121	0.0130	0.0124	0.0122
8	0.0153	0.0147	0.0149	0.0154	0.0149	0.0144	0.0137	0.0132

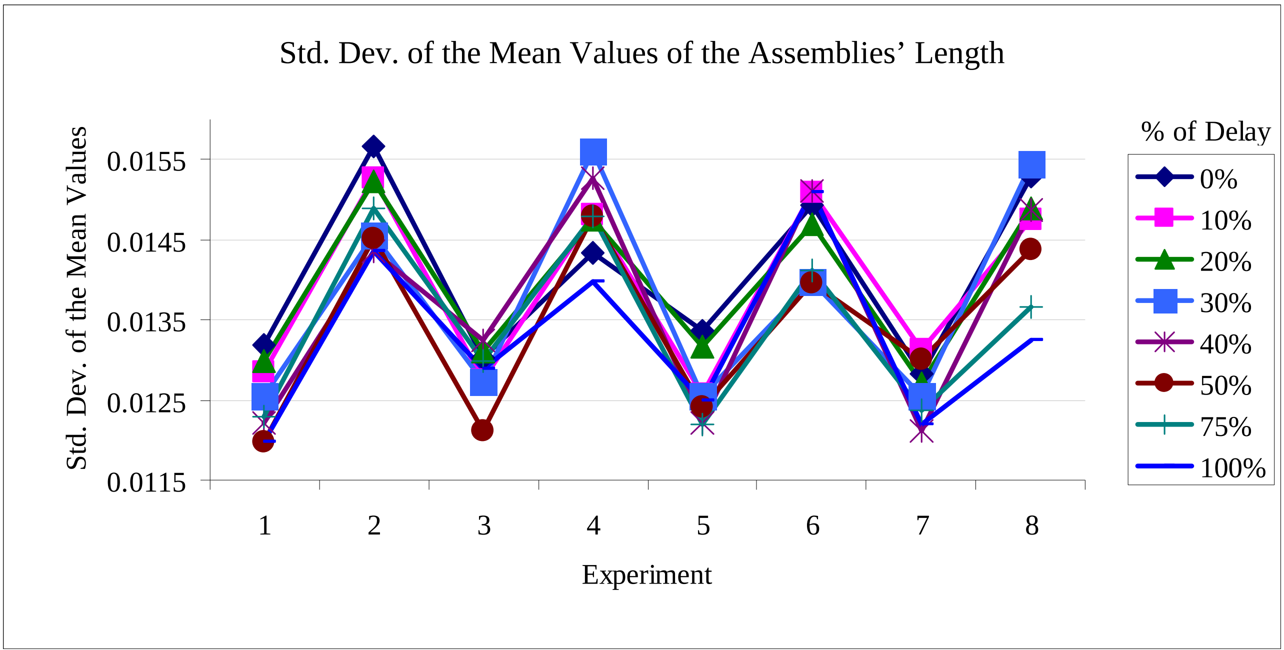


Figure 5-22. Standard deviation of the mean values of the assemblies' length.

Table 5-28. Std. Dev. of the Standard Deviation Values of the Assemblies' Length

Exp.	Response Delay							
	0%	10%	20%	30%	40%	50%	75%	100%
1	0.0049	0.0055	0.0053	0.0057	0.0055	0.0060	0.0062	0.0063
2	0.0050	0.0054	0.0057	0.0061	0.0060	0.0059	0.0064	0.0069
3	0.0052	0.0053	0.0058	0.0055	0.0056	0.0060	0.0064	0.0065
4	0.0052	0.0054	0.0055	0.0057	0.0062	0.0065	0.0065	0.0067
5	0.0051	0.0052	0.0055	0.0058	0.0060	0.0058	0.0061	0.0063
6	0.0052	0.0053	0.0056	0.0059	0.0061	0.0061	0.0065	0.0070
7	0.0051	0.0056	0.0053	0.0059	0.0056	0.0058	0.0061	0.0064
8	0.0052	0.0053	0.0059	0.0058	0.0061	0.0064	0.0067	0.0066

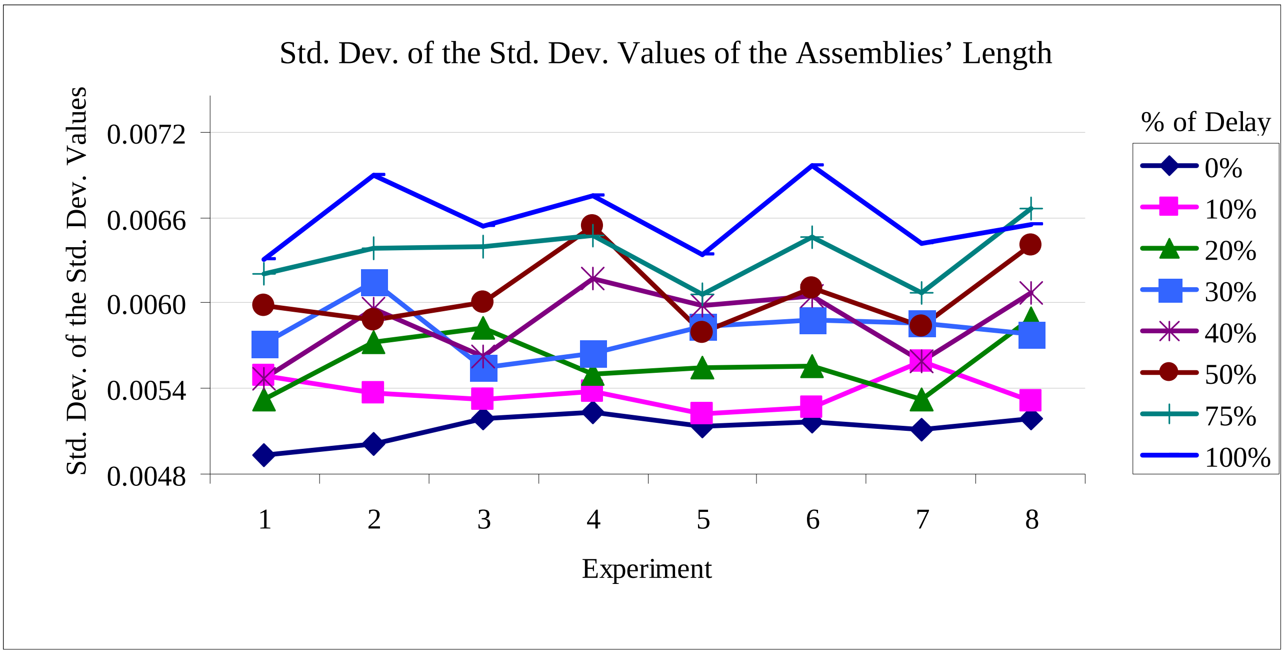


Figure 5-23. Std. Dev. of the standard deviation values of the assemblies' length.

A different way, perhaps more interesting, to visualize the impact of response delays on the parameters studied here is by means of their variation expressed in percentages. Table 5-29 presents these data, which can be visualized in Figure 5-24. There, the standard deviation of the mean values seems to be the only parameter not being affected by the response delay. In fact, it slowly decreases up to 6% as the response delay grows from 0% up to 100%. Nonetheless, this fluctuation represents less than athousandth of the mean found in a regular lot.

Table 5-29. Variation of Different Parameters (%)

	Response Delay			
Parameter	25%	50%	75%	100%
Average Shift Mean	14.3%	31.6%	49.0%	64.1%
Average Std. Dev.	7.4%	15.9%	24.2%	33.1%
Std. Dev. of Mean Values	-1.4%	-4.6%	-4.9%	-6.2%
Std. Dev. of Std. Dev. Values	8.9%	19.9%	24.9%	30.6%

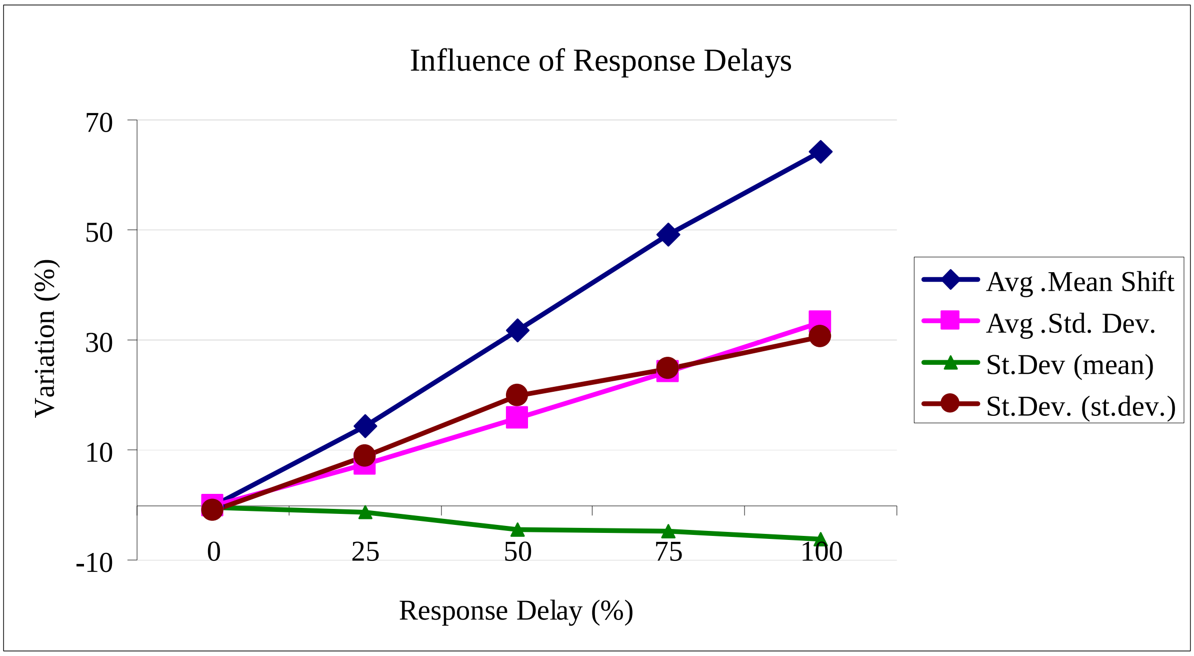


Figure 5-24. Influence of response delays on the parameters of interest.

Simulation results showed that, just like classical control models, the performance of the proposed feed-forward controller, in terms of the systems output, is affected by the presence of response delays and that the impact is proportional to the delays' length.

Process capability indices, potential and actual, can be also used to quantify the influence of response delays. In both cases, Table 5-30 and Table 5-31, it is evident that the simulated process looses capability in the presence of response delays (Figure 5-25 and Figure 5-26).

Table 5-30. Influence of the Response Delay on the Potential Capability Index c_p

Exp.	Response Delay							
	0%	10%	20%	30%	40%	50%	75%	100%
1	1.3610	1.3237	1.2885	1.2521	1.2158	1.1796	1.1041	1.0311
2	1.3565	1.3192	1.2812	1.2401	1.2079	1.1687	1.0893	1.0192
3	1.3587	1.3245	1.2886	1.2506	1.2160	1.1820	1.1047	1.0326
4	1.3582	1.3190	1.2804	1.2407	1.2059	1.1682	1.0922	1.0181
5	1.3578	1.3247	1.2876	1.2498	1.2149	1.1798	1.1052	1.0300
6	1.3532	1.3170	1.2804	1.2393	1.2063	1.1690	1.0919	1.0181
7	1.3592	1.3232	1.2887	1.2506	1.2162	1.1814	1.1035	1.0317
8	1.3554	1.3186	1.2826	1.2406	1.2063	1.1716	1.0925	1.0191

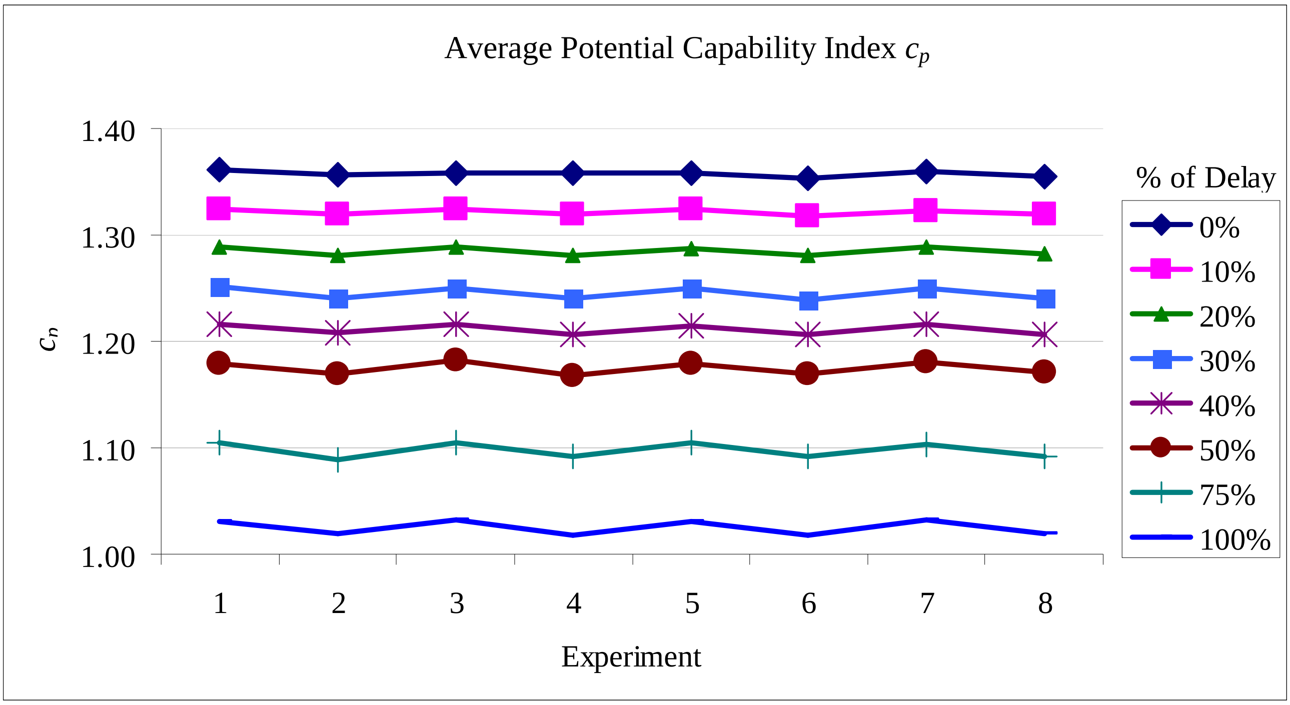


Figure 5-25. Influence of the response delay on the potential capability index c_p.

Table 5-31. Influence of the Response Delay on the Actual Capability Index c_{pk}

Exp.	Response Delay							
	0%	10%	20%	30%	40%	50%	75%	100%
1	1.2910	1.2526	1.2162	1.1775	1.1401	1.1021	1.0231	0.9475
2	1.2961	1.2570	1.2179	1.1756	1.1393	1.1001	1.0178	0.9444
3	1.2886	1.2534	1.2168	1.1763	1.1400	1.1045	1.0243	0.9482
4	1.2965	1.2570	1.2182	1.1747	1.1383	1.1002	1.0195	0.9433
5	1.2890	1.2526	1.2154	1.1767	1.1389	1.1026	1.0238	0.9476
6	1.2913	1.2554	1.2157	1.1724	1.1380	1.0998	1.0184	0.9433
7	1.2911	1.2514	1.2154	1.1755	1.1399	1.1033	1.0224	0.9481
8	1.2963	1.2564	1.2202	1.1760	1.1390	1.1016	1.0187	0.9439

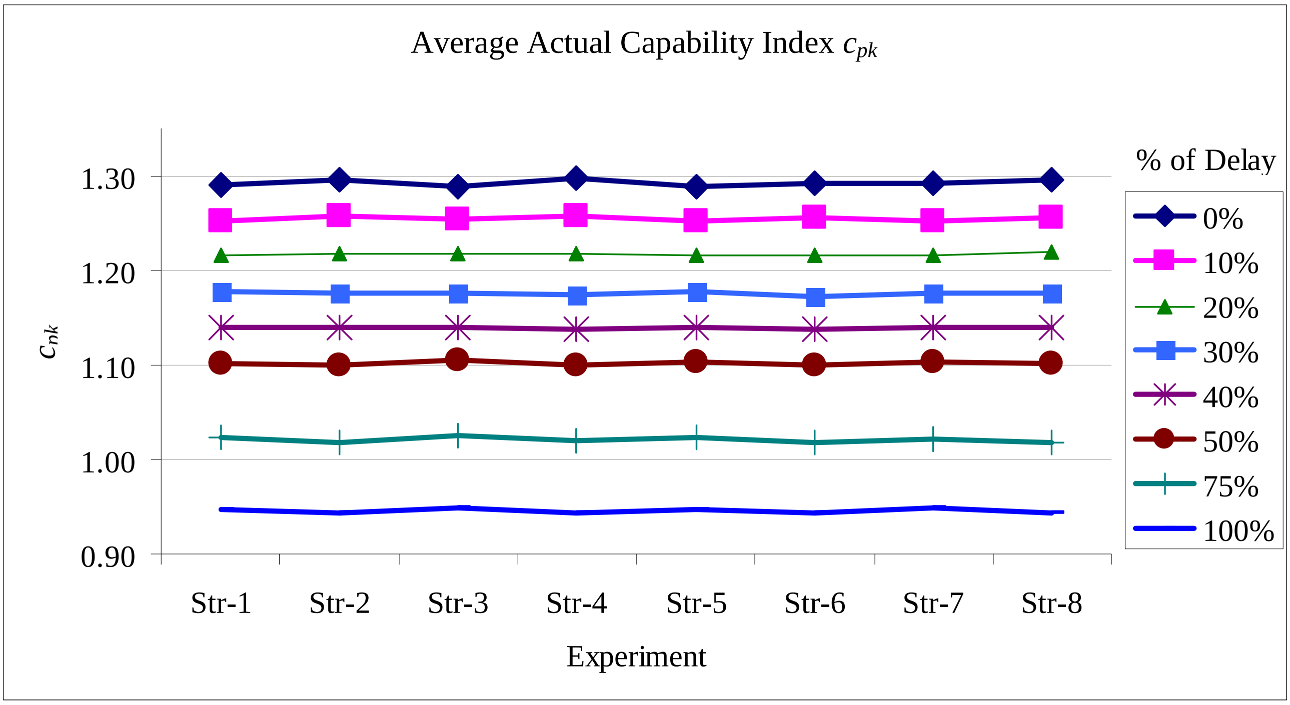


Figure 5-26. Influence of the response delay on the actual capability index c_{pk}.

5.3.6. SFFCM in Parallel Manufacturing Systems

The purpose of these experiments is to evaluate effectiveness of the proposed SFFCM-based assembling technique in a parallel manufacturing system. In this case, whereas the inspection rate remained fixed at 20%, the subset size was set to 50, 100, 125 and 200. For each value of the subset size, the simulation of the experiments in Table 5-32 was replicated 500 times. In this opportunity, only the sample mean was used as central tendency measure.

Table 5-32 presents the definition of the experiments simulated in this stage of the research. This table presents three additional columns in which the prediction mode is specified. Three predictive algorithms were developed: simple prediction based on the measurements made on last inspected subset, prediction based on a robust regression algorithm and prediction based on the construction of polynomials of second degree. In the last two cases, all the available data were used to compute the predictions, from subset *1* to subset *i*.

Table 5-32. Design of Experiments for Parallel Manufacturing

Exp.	Random Sampling		Subset Pattern		Prediction Mode		
	Simple	System	Common	Individual	Simple	Robust Reg.	Polynomial
1	√		√		√		
2	√		√			√	
3	√		√				√
4	√			√	√		
5	√			√		√	
6	√			√			√
7		√	√		√		
8		√	√			√	
9		√	√				√
10		√		√	√		
11		√		√		√	
12		√		√			√

In a parallel system, component items are supposed to be manufactured simultaneously in different lines. Therefore, an adjustment computed with data retrieved from a given subset *i* of Component 1 can not be applied instantaneously to the matching subset *i* of Component 2, though perhaps to a subsequent subset *(i+1)*. To overcome the offset problem, the use of prediction algorithms is proposed.

Table 5-33. Average Sample Mean of the Resulting Assemblies' Length

Exp.	Subset Size			
	50	100	125	200
1	29.9343	29.9237	29.9205	29.9034
2	29.9512	29.9221	29.9106	29.8645
3	29.8903	29.8550	29.8490	29.8137
4	29.9375	29.9253	29.9210	29.9046
5	29.9535	29.9200	29.9162	29.8715
6	29.8918	29.8552	29.8454	29.8125
7	29.9373	29.9247	29.9195	29.9062
8	29.9577	29.9243	29.9163	29.8651
9	29.8880	29.8536	29.8472	29.8132
10	29.9356	29.9233	29.9197	29.9032
11	29.9547	29.9221	29.9142	29.8747
12	29.8898	29.8548	29.8480	29.8108

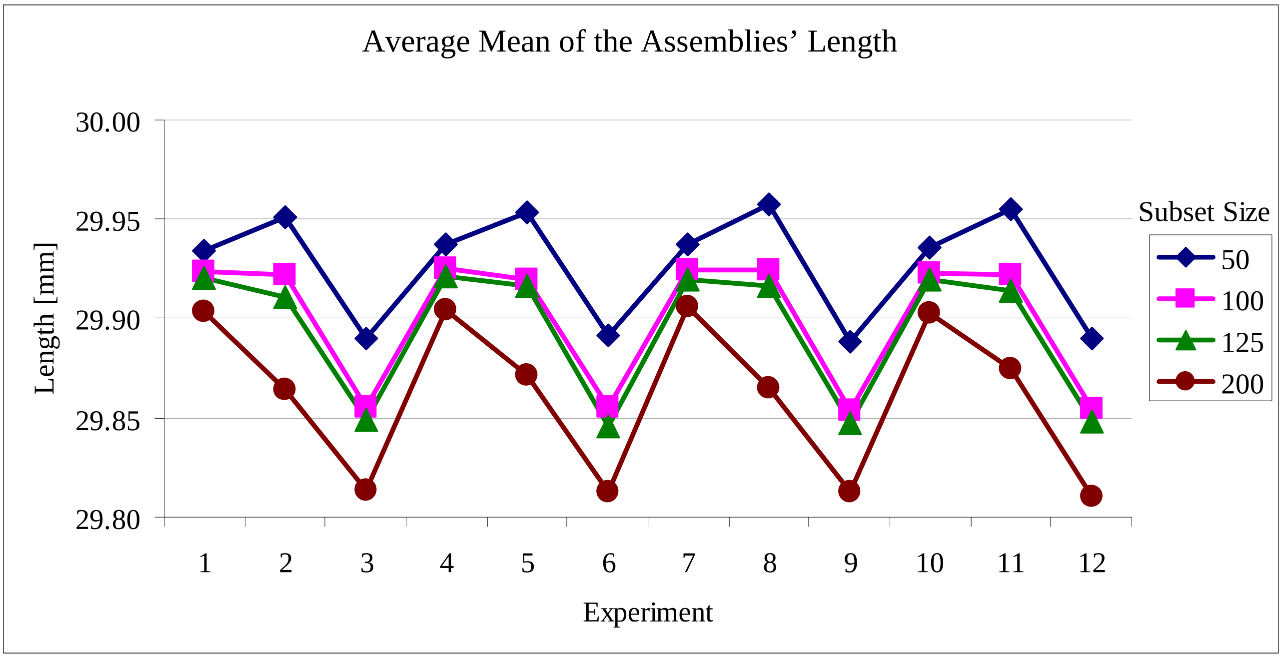


Figure 5-27. Average sample mean of the resulting assemblies' length.

From Table 5-33 and Table 5-34 it seems clear that the subset size is an influential factor also in parallel system since the average mean shift and the average standard deviation decrease in concordance with the reduction of the subset size. These imply, however, more costly adjustments. Besides that, the experiments showed that neither the robust regression nor the polynomial prediction modes were able to improve the results achieved by the simple prediction mode (experiments 1, 4, 7 and 10).

Table 5-34. Average Std. Dev. of the Resulting Assemblies' Length

Exp.	Subset Size			
	50	100	125	200
1	0.2776	0.3063	0.3231	0.3694
2	0.3219	0.3827	0.4124	0.4777
3	0.3123	0.3682	0.3954	0.4520
4	0.2780	0.3065	0.3221	0.3707
5	0.3199	0.3824	0.4163	0.4846
6	0.3141	0.3668	0.3942	0.4527
7	0.2785	0.3069	0.3235	0.3709
8	0.3213	0.3845	0.4160	0.4790
9	0.3155	0.3699	0.3965	0.4530
10	0.2768	0.3062	0.3234	0.3703
11	0.3194	0.3825	0.4137	0.4851
12	0.3143	0.3689	0.3950	0.4514

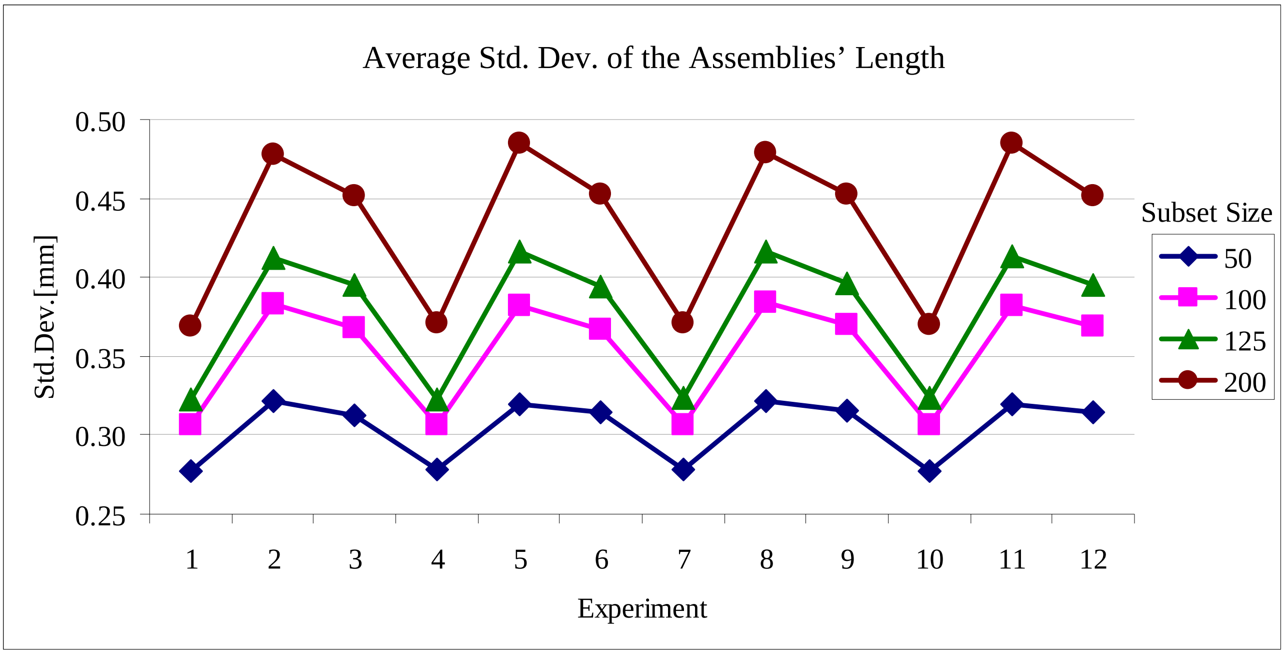


Figure 5-28. Average standard deviation of the resulting assemblies' length.

With the exemption of the average shift mean obtained when setting the subset size to 50, the experiments showed that the simple prediction is the best alternative considering the particular conditions of the simulation. This does not mean that in all cases the simple prediction should be selected. That decision will depend mostly on the particular characteristics of the variation under observation.

In particular, experiments 1, 4, 7 and 10 delivered the best results in most of the cases (Table 5-35 and Table 5-36). From the proposed prediction alternatives, only the simple prediction mode produced reductions in the average mean shift and in the average standard deviation that were maintained consistently through out massive replications. In this specific point, the prediction mode based on a robust regression algorithm delivered the poorest results as it is shown in the experiments 2, 5, 8 and 11.

Table 5-35. St. Dev. of the Sample Mean Values of the Resulting Assemblies' Length

Exp.	Subset Size			
	50	100	125	200
1	0.0127	0.0131	0.0127	0.0134
2	0.0260	0.0298	0.0319	0.0308
3	0.0183	0.0174	0.0178	0.0175
4	0.0123	0.0126	0.0130	0.0129
5	0.0250	0.0285	0.0295	0.0346
6	0.0174	0.0155	0.0153	0.0200
7	0.0133	0.0122	0.0130	0.0119
8	0.0259	0.0284	0.0289	0.0322
9	0.0182	0.0187	0.0172	0.0197
10	0.0125	0.0130	0.0124	0.0124
11	0.0260	0.0302	0.0302	0.0317
12	0.0188	0.0167	0.0165	0.0193

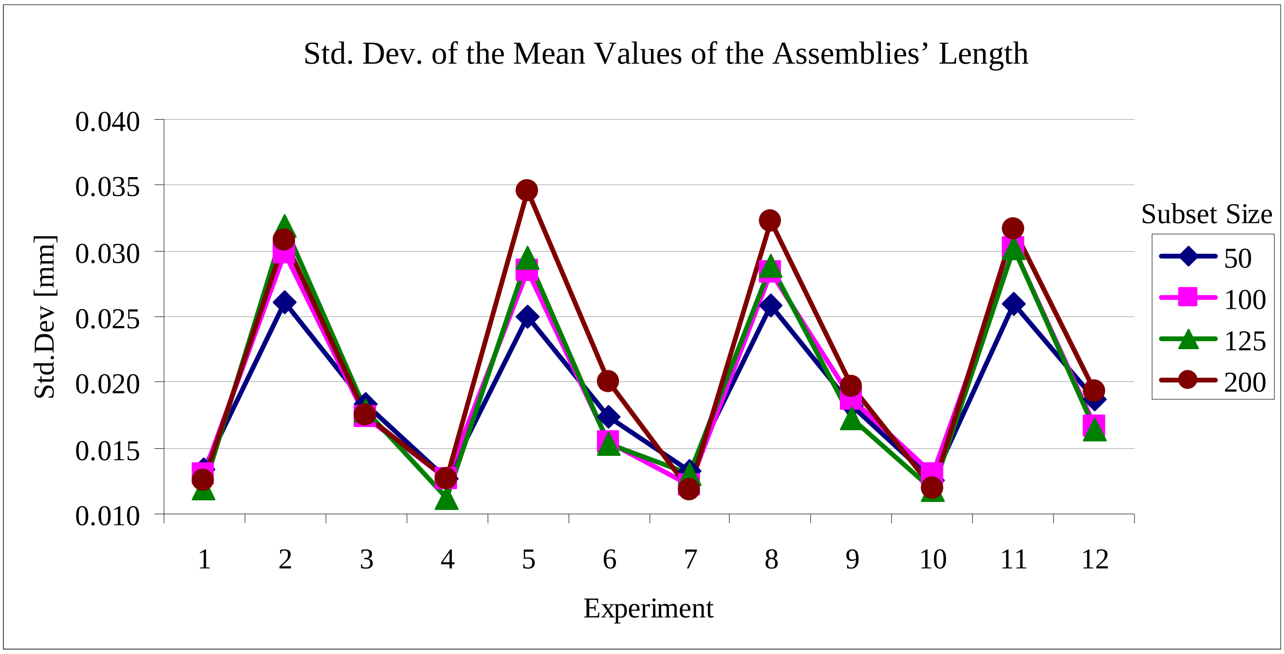


Figure 5-29. Std. Dev. of the mean values of the resulting assemblies' length.

Table 5-36. St. Dev. of the Standard Deviation Values of the Resulting Assemblies' Length

Exp.	Subset Size			
	50	100	125	200
1	0.0064	0.0063	0.0068	0.0076
2	0.0106	0.0131	0.0147	0.0226
3	0.0079	0.0107	0.0112	0.0152
4	0.0060	0.0062	0.0067	0.0073
5	0.0071	0.0118	0.0130	0.0255
6	0.0094	0.0106	0.0118	0.0154
7	0.0064	0.0063	0.0067	0.0070
8	0.0098	0.0122	0.0133	0.0231
9	0.0107	0.0122	0.0134	0.0172
10	0.0061	0.0065	0.0070	0.0070
11	0.0090	0.0105	0.0138	0.0256
12	0.0107	0.0131	0.0134	0.0162

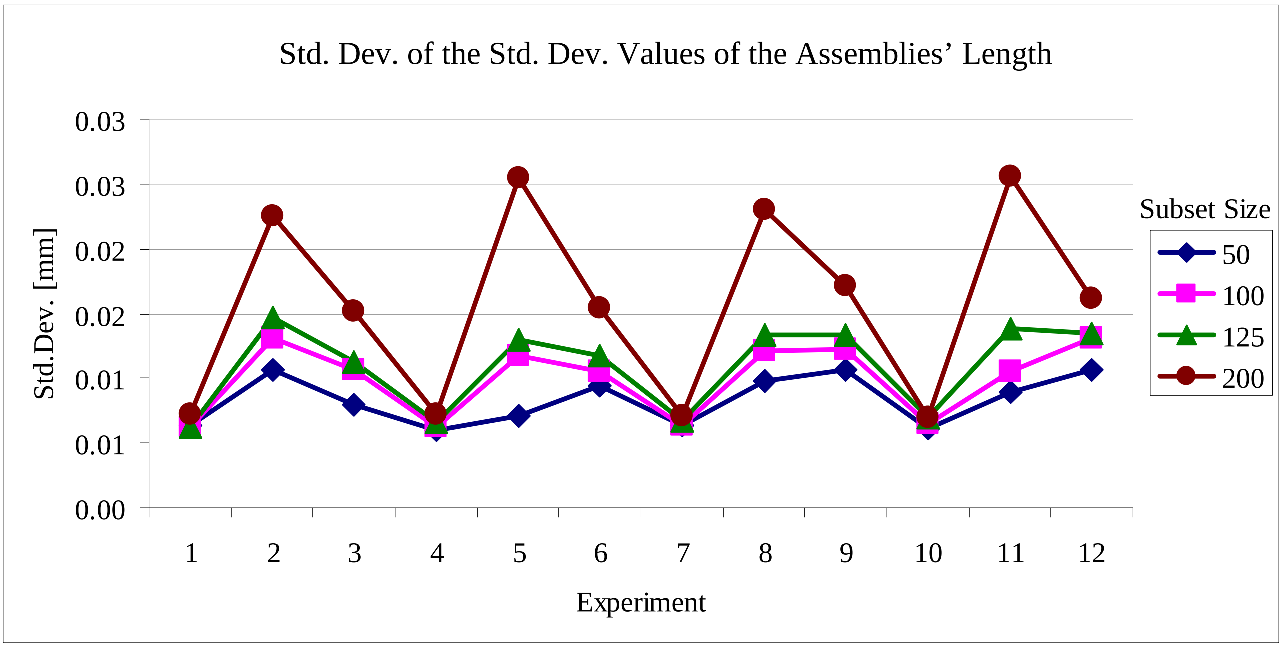


Figure 5-30. Std. Dev. of the standard deviation values of the resulting assemblies' length.

A quick look at the process capability indices c_p and c_{pk} is always helpful to visualize the influence of the factors under study on the parameters of interest. Since the potential capability index does not consider the shift of the mean, it is always recommendable not to forget to have a look at the actual capability index c_{pk} as well. As explained in previous chapter, a process is considered as capable when it exhibits a c_p higher than 1.33 and it will be considered under control when its index c_{pk} is a comparable value [Pfe02 ch.5 p.390].

Table 5-37. Potential Capability Index c_p

Exp.	Subset Size			
	50	100	125	200
1	1.2009	1.0883	1.0318	0.9022
2	1.0356	0.8709	0.8083	0.6978
3	1.0672	0.9054	0.8430	0.7374
4	1.1991	1.0875	1.0348	0.8991
5	1.0419	0.8717	0.8008	0.6878
6	1.0614	0.9087	0.8457	0.7363
7	1.1969	1.0862	1.0305	0.8988
8	1.0375	0.8670	0.8013	0.6960
9	1.0566	0.9011	0.8407	0.7359
10	1.2043	1.0887	1.0307	0.9001
11	1.0437	0.8714	0.8057	0.6872
12	1.0607	0.9036	0.8439	0.7384

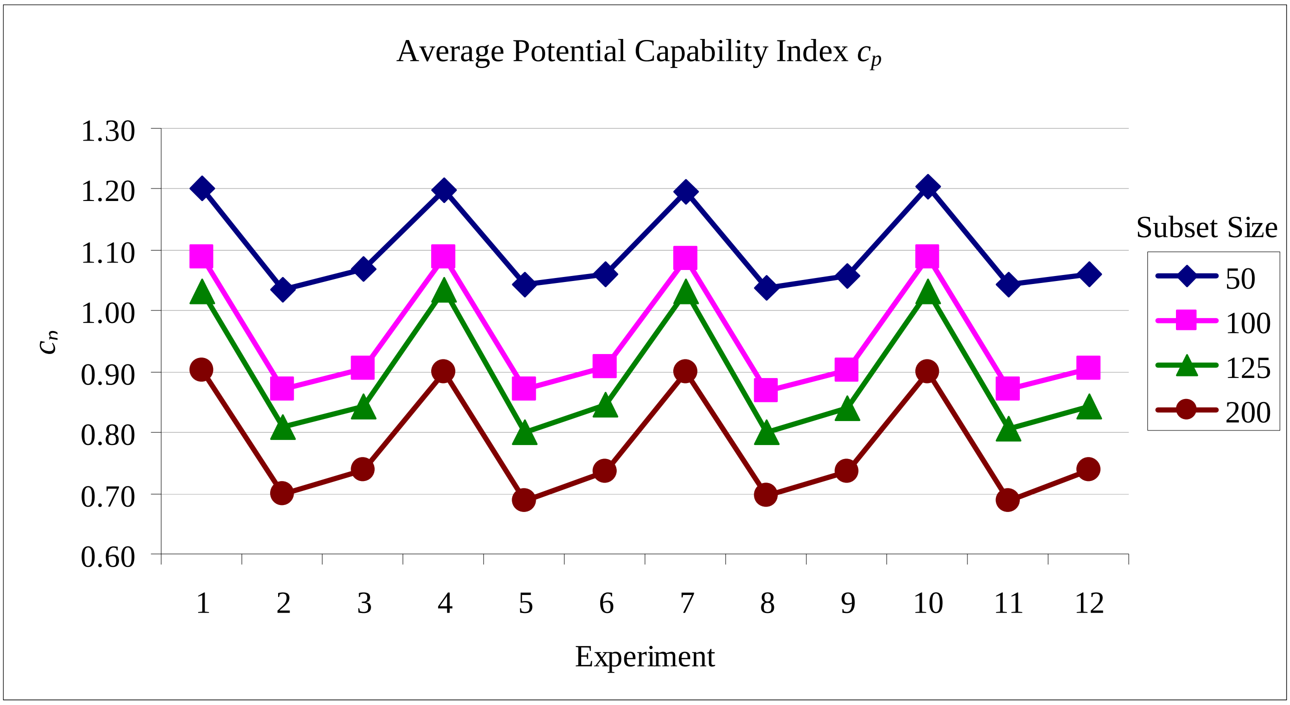


Figure 5-31. Potential capability index c_p as function of the subset size.

In this particular case, Figure 5-31 and Figure 5-32, reveals that the process indices reached values close to 1.33 in those experiments were the simple prediction mode was applied (experiments 1, 4, 7 and 10) only when the subset size was set to 50, i.e., 20 adjustments per lot. This means that a great inspection effort is necessary to obtained results close to those ones achieved with only 8 adjustments in the absence of the offset problem. This time, however, the indices are not good enough to reach the category of capable process.

Table 5-38. Actual Capability Index c_{pk}

Exp.	Subset Size			
	50	100	125	200
1	1.1221	1.0053	0.9497	0.8151
2	0.9851	0.8031	0.7361	0.6032
3	0.9501	0.7741	0.7157	0.6000
4	1.1242	1.0063	0.9531	0.8133
5	0.9934	0.8019	0.7337	0.5994
6	0.9466	0.7771	0.7149	0.5982
7	1.1218	1.0044	0.9475	0.8145
8	0.9937	0.8014	0.7342	0.6021
9	0.9383	0.7692	0.7123	0.5984
10	1.1267	1.0051	0.9480	0.8130
11	0.9964	0.8035	0.7366	0.6011
12	0.9438	0.7724	0.7157	0.5987

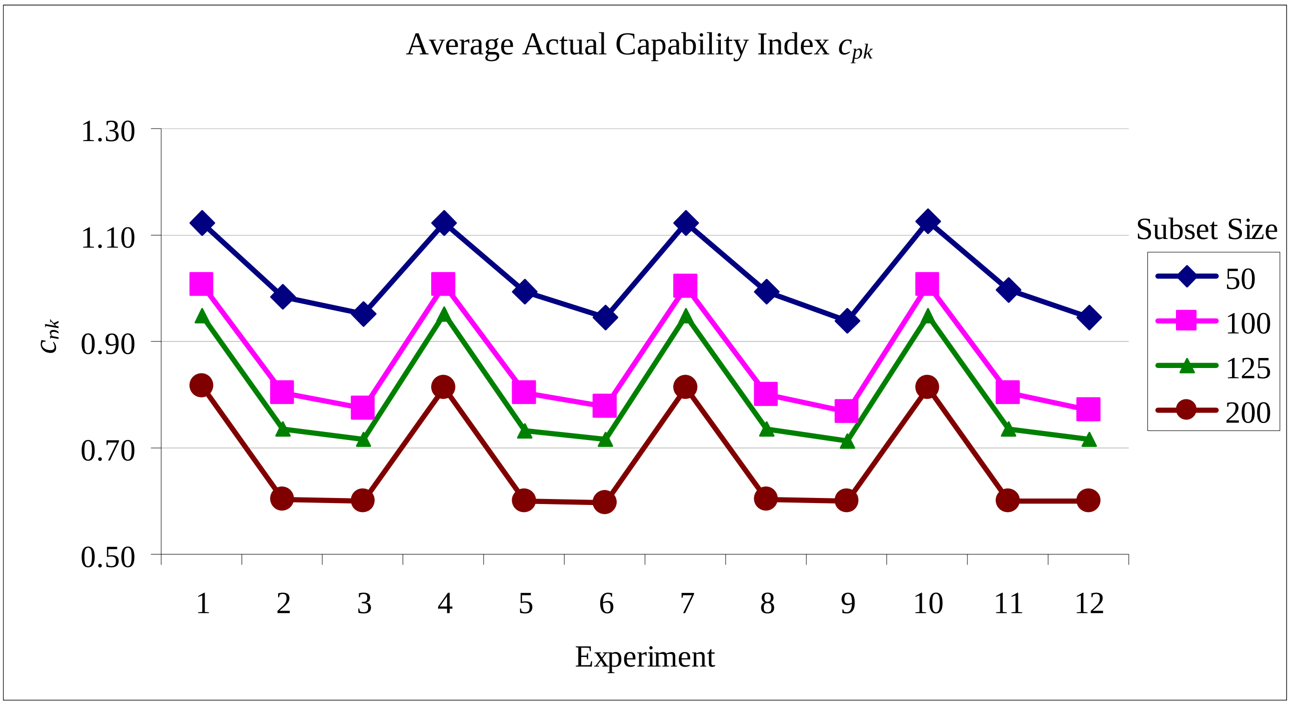


Figure 5-32. Actual capability index c_{pk} as function of the subset size.

Although none of the experiments produced an index c_p higher than 1.33, there was an undeniable improvement in the capability indices after applying the proposed SFFCM-based assembling technique. Especially significant is the variation achieved in c_{pk} as direct consequence of the reduction of the mean shift. The process used to have a $c_{p,assy}$ of 1.15 and a $c_{pk,assy}$ of 0.63. After applying SFFCM, in the best case (experiment 10 and subset size of 50) $c_{p,assy,adj}$ increased by 4.7%, whereas $c_{pk,assy,adj}$ did it by 78.2% (*hint: the subscript adj indicates that the value was obtained after applying SFFCM*).

The importance of improving c_{pk} , in spite of the poor improvement of c_p , strives in the closeness of the resulting mean to the nominal target. Now, the area under the curve of the probability density function (PDF) between the tolerance limits is larger, which implies that a lower number of assemblies out of tolerance are expected to be produced. Before applying SFFCM, the process used to produce an average of 28.6 assemblies out of tolerance per 1,000 opportunities. With the help of the SFFCM, instead, it was possible to reduce this rate by 93% up to 2 units per 1,000 opportunities. This was achieved in the experiments 1, 4, 7 and 10 when the subset size was set to 50 as it is shown in Table 5-39.

Table 5-39. Average Number of Assemblies out of Tolerance

Exp.	Subset Size			
	50	100	125	200
1	2.0	4.9	6.9	12.2
2	5.2	12.6	16.3	25.6
3	4.8	12.7	16.8	24.8
4	2.2	4.9	6.8	12.1
5	4.8	12.0	16.9	26.3
6	5.0	12.0	16.5	25.6
7	2.2	4.4	6.6	12.3
8	4.4	12.5	16.5	25.3
9	5.2	12.5	16.1	24.8
10	2.0	4.6	6.4	11.9
11	4.6	12.1	16.3	25.9
12	4.7	12.7	16.1	24.9

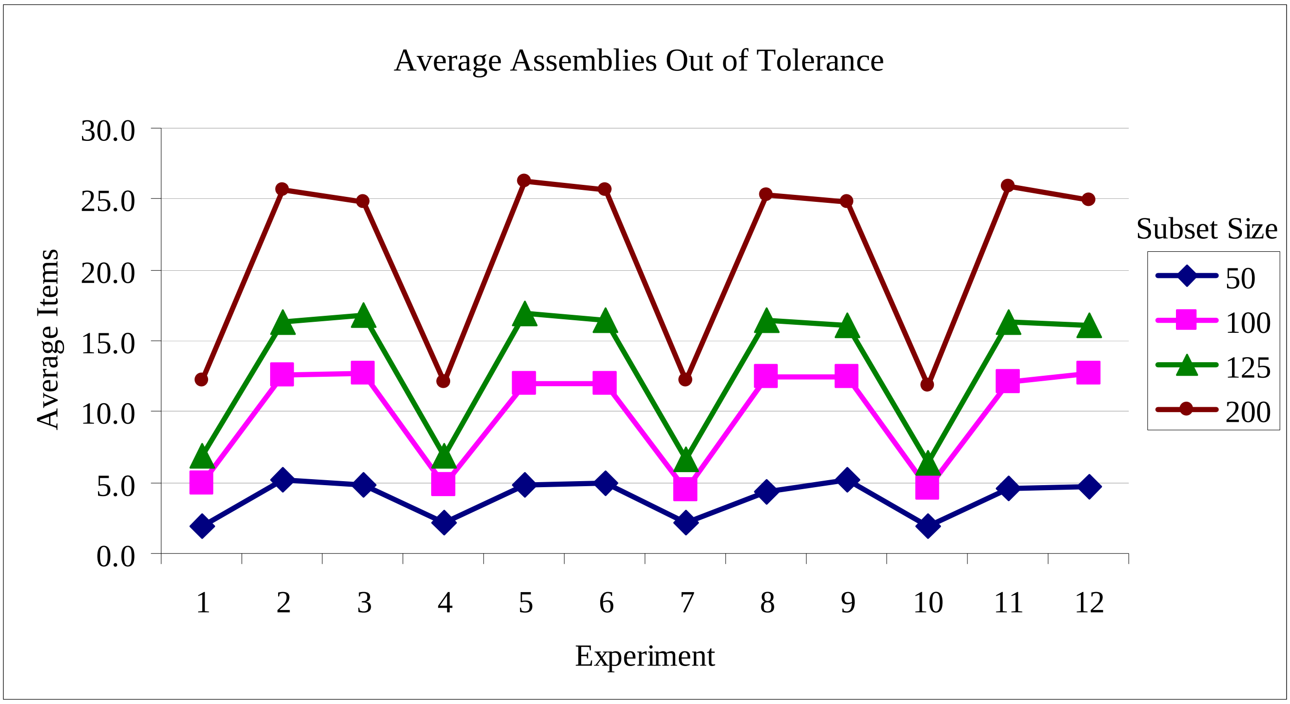


Figure 5-33. Average number of assemblies out of tolerance.

It is rather interesting to compare the simulation results before and after applying SFFCM with and without the inclusion of the offset problem (Table 5-40).

Table 5-40. Comparison - SFFCM With and Without Offset

	No SFFCM Randomized Assembling	SFFCM No Offset	SFFCM Offset
Avg. Mean	29.5500	29.9485	29.9577
Avg. St. Dev.	0.2900	0.2449	0.2776
Avg. c_p	1.1494	1.3610	1.2043
Avg. c_{pk}	0.6322	1.2961	1.1267
Nr. Adjustments	0	8	20
Avg. Defectives	28.6	0	2

Simulation results showed that none of the prediction algorithms tested in this stage of research was able to overcome completely the offset problem. However, when the subset size was small enough the simple prediction mode delivered systematically good numbers. Albeit, at higher cost in terms of the number of adjustments.

A possible explanation for the low performance of the predicting algorithm might be found in the use of all the available data, from subset *1* to subset *i*, to construct the regression and the polynomial of 2nd order. Data taken from the first few subsets is probably to far back in time and give rise to a biased prediction. A possible strategy to overcome this problem may be the consideration of a limited set of data coming from the last few inspected subsets.

5.3.7. Multi-Component Assembling

The purpose of these experiments is to evaluate the effectiveness of the proposed SFFCM-based assembling technique when a multi-component assembly has to be produced. In this case, the assembly consisted of five components. The measurement sensor was placed at different positions, *k*, so that all the possible alternatives were tested. First, the sensor was placed between Component 1 and Component 2 so that the specifications of the latter were the subject of the adjustment. Then, the sensor was placed after Component 2 as to adjust the specifications of Component 3, and so on. During the simulation the inspection rate remained fixed at 20% and the subset size at 125, i.e., 8 adjustments per lot.

Different from previous simulations where the number of replications was essential to validate the results, in this opportunity all the experiments were carried out using the same lots. Only the position *k* was modified. The reason for doing this is rather practical. Given that every replication requires the generation new lots of items, it would not be easy to quantify the influence of the position *k* by means of analyzing completely different populations.

Whereas the nominal specifications of the multi-component assembly were set to 50.00 ± 1.12 [mm]; the specifications of the components were set to 10.00 ± 0.50 [mm]. Table 5-41 summarizes the nominal specification of the components and the characteristics of the corresponding manufacturing processes that, as usual, were assumed to be non-capable. Table 5-42 presents the definition of the experiments simulated in this stage of the research.

Table 5-41. Nominal Specifications, Process Characteristics and Capability Indices

	Specifications [mm]		Process Characteristics			
	Target	Tolerance	Mean	Std. Dev.	c_p	c_{pk}
Assembly	50.00	1.12	49.75	0.29	1.28	1.00
Component 1	10.00	0.50	9.95	0.13	1.28	1.15
Component 2	10.00	0.50	9.95	0.13	1.28	1.15
Component 3	10.00	0.50	9.95	0.13	1.28	1.15
Component 4	10.00	0.50	9.95	0.13	1.28	1.15
Component 5	10.00	0.50	9.95	0.13	1.28	1.15

Table 5-42. Design of Experiments for Different *k*

Exp.	Random Sampling		Subset Pattern		Tendency Measure Estimator	
	Simple	Systematic	Common	Individual	$\bar{x}_{1,sub}$	$\bar{x}_{1,sub,cdna}$
1	√		√		√	
2	√		√			√
3	√			√	√	
4	√			√		√
5		√	√		√	
6		√	√			√
7		√		√	√	
8		√		√		√

The number *k* is at same time the position of the controller and the position of the component whose specifications will be adjusted. Table 5-43 shows that, in all the experiments, the mean shift of the resulting assemblies' length decreases as *k* increases. Similar behavior is revealed in Table 5-44, where the resulting standard deviation decreased as *k* increases. The interpretation is rather practical. Low values of *k* imply that the adjustments are made on the first components and the effect is lost due to the variation added by the remaining components. High values of *k* imply that the adjustments are applied at the end of the assembling line and, therefore, the corrective adjustments are not affected by the eventual assembling of the few remaining components.

In this simulation, each experiment was allocated particular fixed lots of components so that the only modification to the experiment setup was the position of the controller, the number *k*. For this reason, a crossed comparison among experiments lacks of sense. The only meaningful possible comparison is between different positions *k* of the feed-forward controller.

In Figure 5-34 and Figure 5-35 a curve corresponding to *k=0* has been included. It represents the result of carrying out a fully randomized assembling in the absence of the proposed SFFCM. This helps visualize that whichever the controller position, the application of SFFCM is always beneficial. The fluctuation described by the curve *k=0* may be attributed to the randomness of both the lots creation and the assembling itself, which is expected to give rise to different numbers.

Table 5-43. Mean of the Assemblies' Length

Exp.	Adjusted Component *k-th*			
	k = 2	*k = 3*	*k = 4*	*k = 5*
1	49.7869	49.8404	49.8833	49.9306
2	49.8045	49.8563	49.9110	49.9532
3	49.7779	49.8299	49.8731	49.9346
4	49.8078	49.8520	49.9114	49.9529
5	49.7935	49.8432	49.9040	49.9568
6	49.7847	49.8458	49.9041	49.9455
7	49.8072	49.8466	49.8987	49.9452
8	49.7990	49.8690	49.9141	49.9686

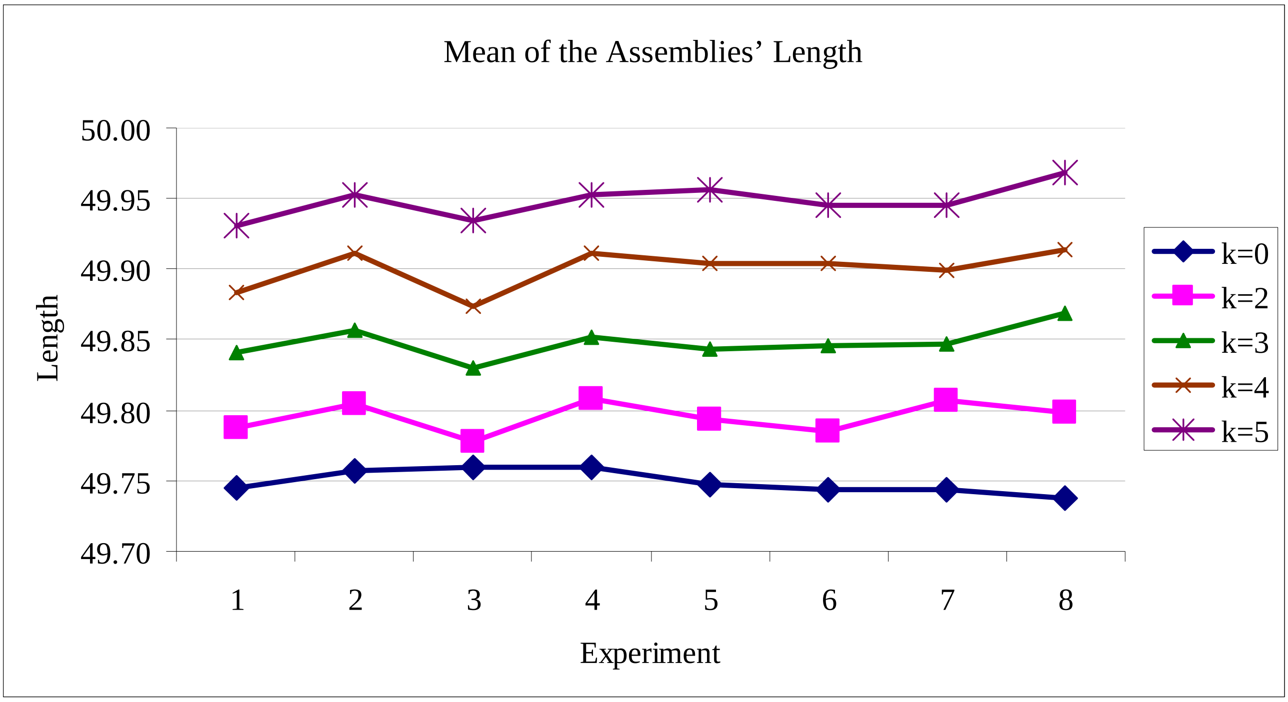


Figure 5-34. Mean of the resulting assemblies' length.

Table 5-44. Std. Dev. of the Assemblies' Length

Exp.	Adjusted Component *k-th*			
	k = 2	*k = 3*	*k = 4*	*k = 5*
1	0.2795	0.2670	0.2564	0.2453
2	0.2734	0.2641	0.2483	0.2384
3	0.2789	0.2559	0.2563	0.2375
4	0.2902	0.2694	0.2555	0.2327
5	0.2681	0.2580	0.2530	0.2406
6	0.2731	0.2729	0.2520	0.2524
7	0.2759	0.2623	0.2507	0.2424
8	0.2709	0.2623	0.2519	0.2454

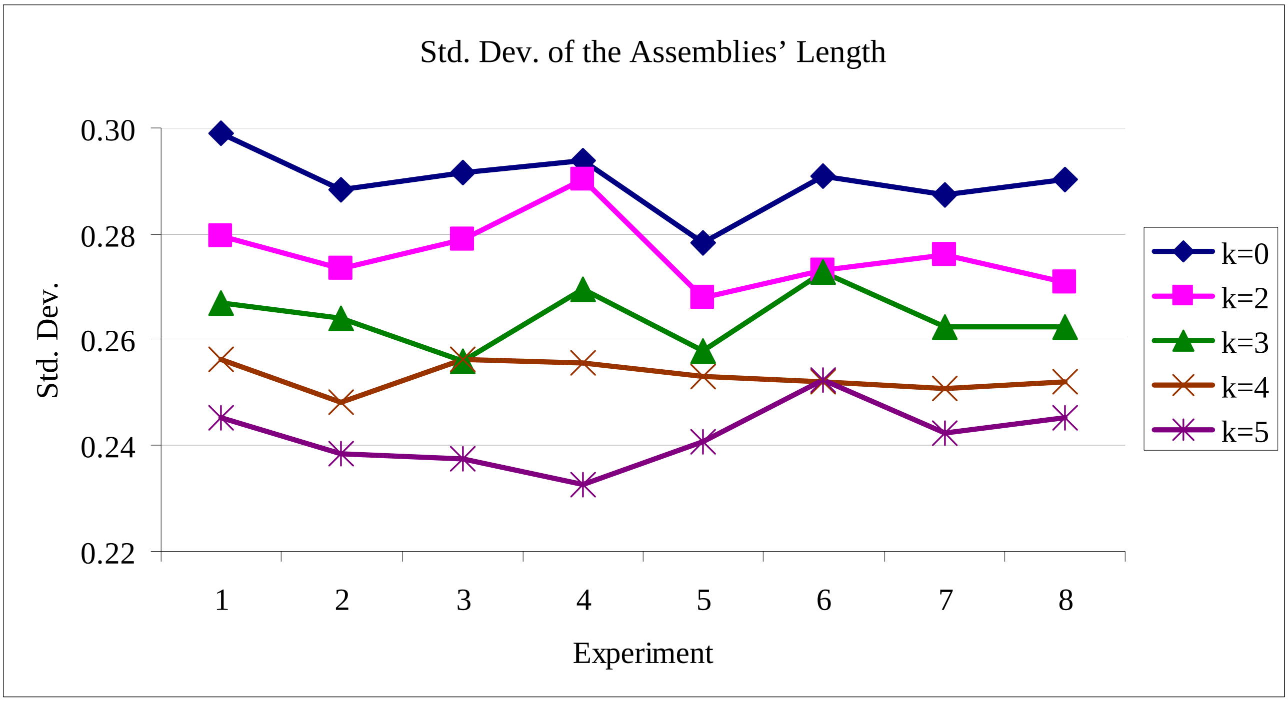


Figure 5-35. Standard deviation of the resulting assemblies' length.

Process capability indices, Table 5-45 and Table 5-46, confirm the tendency found before. The effectiveness of the proposed SFFCM-based technique increases when the adjustments are made at the end of the assembling line as it is shown in Figure 5-36 and Figure 5-37 for the potential and actual capability index respectively.

Table 5-45. Potential Capability Index c_p

Exp.	Adjusted Component *k-th*			
	k = 2	*k = 3*	*k = 4*	*k = 5*
1	1.3358	1.3984	1.4559	1.5219
2	1.3656	1.4136	1.5035	1.5663
3	1.3386	1.4588	1.4566	1.5722
4	1.2867	1.3857	1.4611	1.6042
5	1.3926	1.4468	1.4756	1.5518
6	1.3670	1.3678	1.4815	1.4792
7	1.3533	1.4231	1.4889	1.5404
8	1.3782	1.4230	1.4820	1.5213

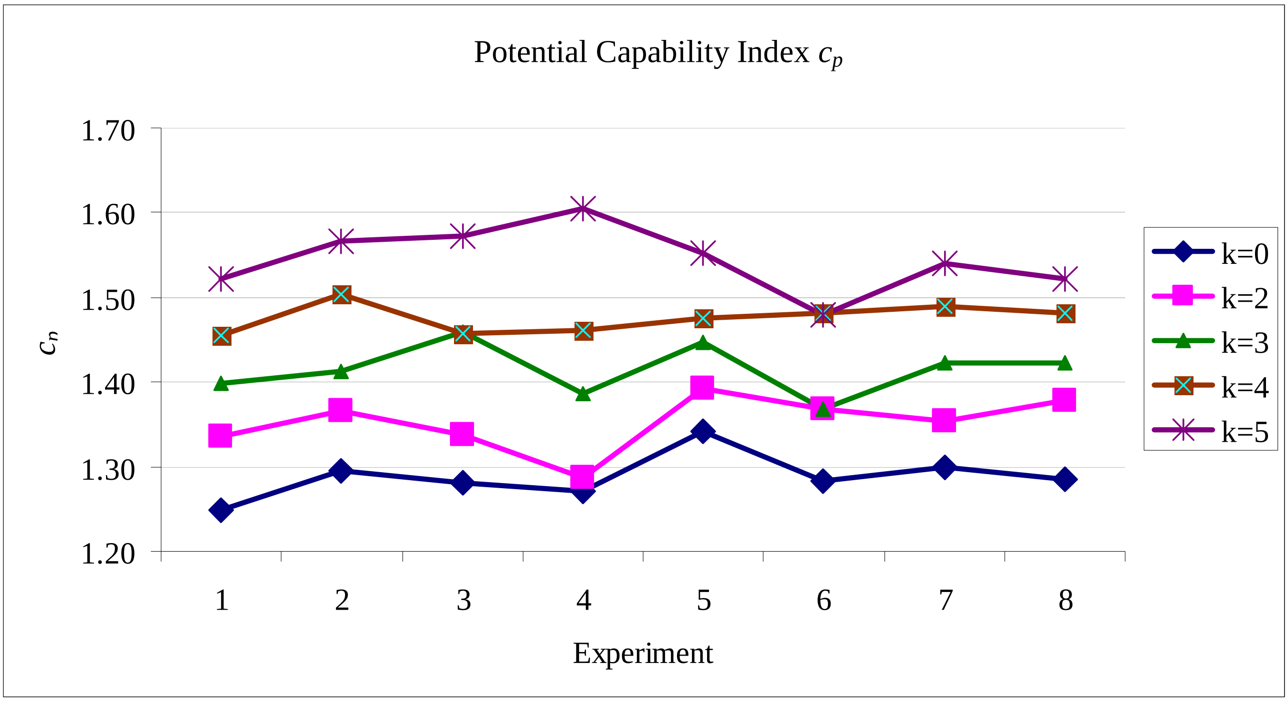


Figure 5-36. Potential Capability Index c_p.

Table 5-46. Actual Capability Index c_{pk}

Exp.	Adjusted Component *k-th*			
	k = 2	*k = 3*	*k = 4*	*k = 5*
1	1.0816	1.1992	1.3042	1.4275
2	1.1272	1.2322	1.3840	1.5008
3	1.0731	1.2372	1.2916	1.4805
4	1.0659	1.2026	1.3456	1.5367
5	1.1358	1.2443	1.3492	1.4919
6	1.1043	1.1795	1.3546	1.4073
7	1.1203	1.2282	1.3542	1.4650
8	1.1308	1.2566	1.3683	1.4786

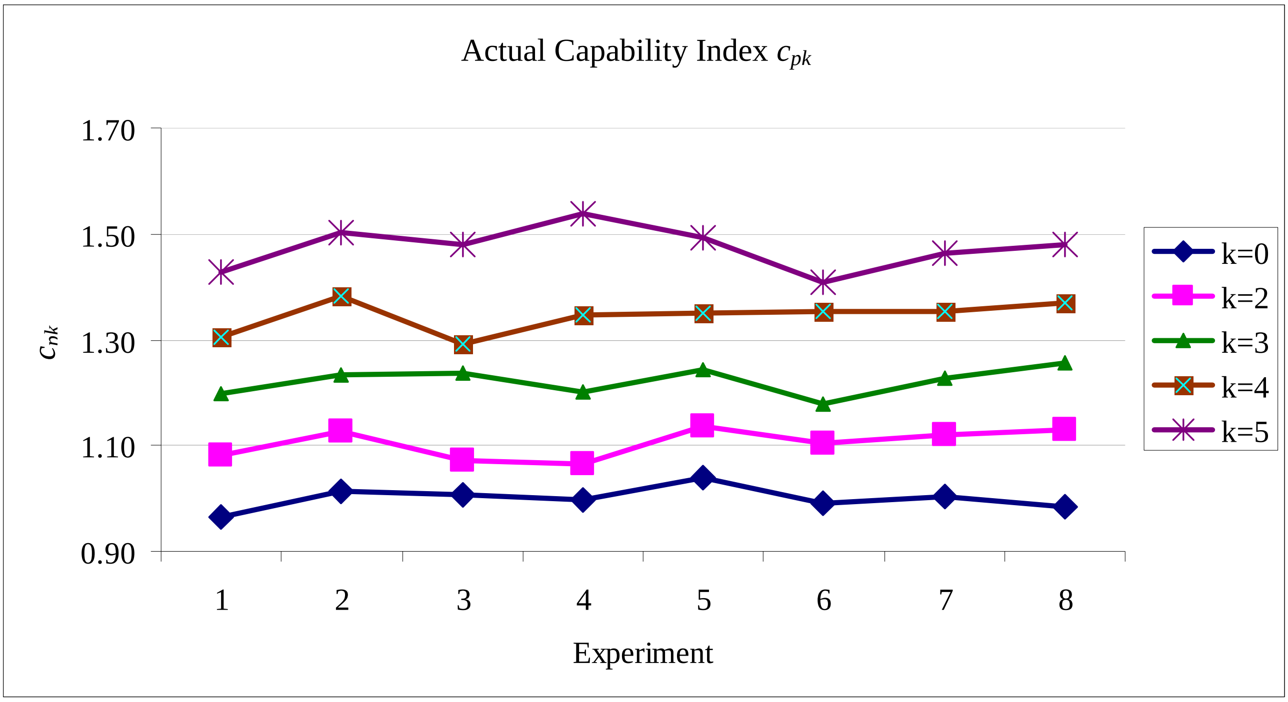


Figure 5-37. Actual Capability Index c_{pk}.

In Figure 5-38, the curves of the probability density distribution (PDF) of the resulting assemblies' length for different values of *k*, corresponding to the experiment 2, are presented. There, the reduction of the mean shift decreases as the controller position *k* approaches the end of the assembling line.

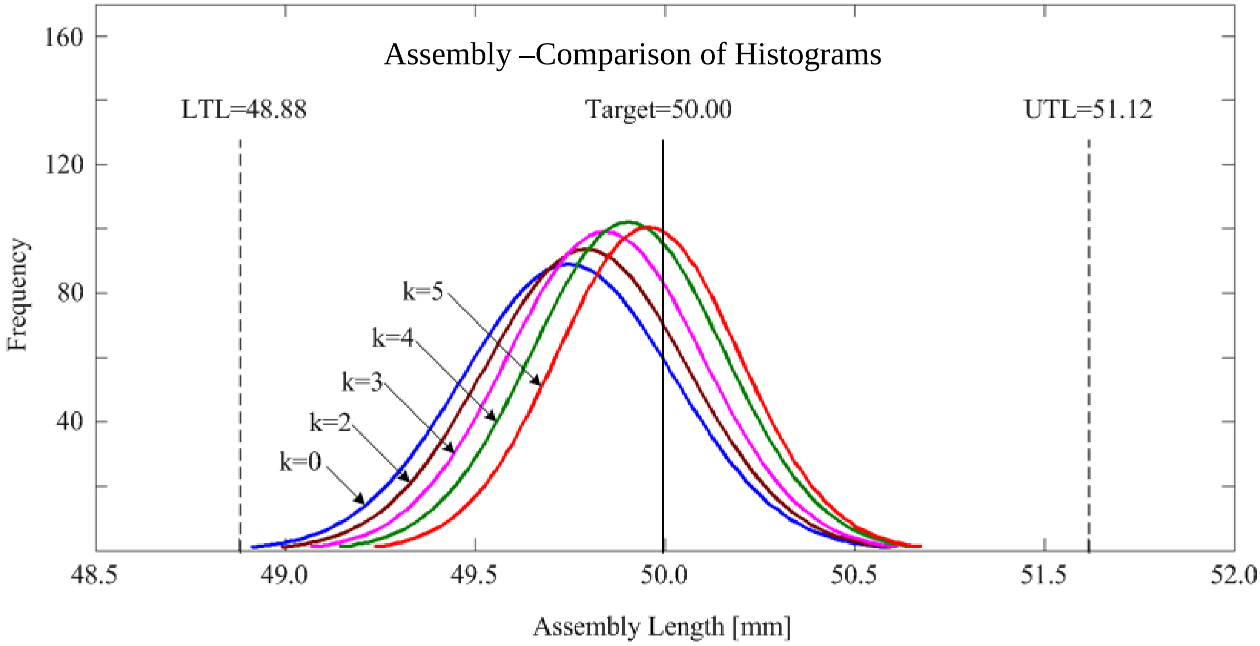


Figure 5-38. Comparison of histograms for different values of *k* (experiment 2).

5.3.8. Complementary External Feedback Loop

The purpose of these experiments is to quantify the impact of an additional external feedback loop in the effectiveness of the proposed SFFCM-based assembling technique. In this case, the subset size was set to 125 and the inspection rate was set to 20%.

Whereas the setting the feed-forward controller obeys to the usual definition of experiments (Table 5-47); the external feedback controller performs a randomized sampling to estimate the sample mean, which is used then as estimator of the central tendency measure. The simulation of each experiment was replicated 500 times.

Basically, the external feedback controller samples randomly some of the finished assemblies from each subset *i* using same the inspection rate defined for the feed-forward controller (20%) so that the subsequent subset *(i+1)* of items of Component 2 can be adjusted also in proportion to the difference found between the assembly nominal target, L_{assy}, and the measured assembly sample mean. Thus, data retrieved from both the feed-forward and the feedback controller can be used to determine the necessary adjustments. Table 5-47 presents the definition of the experiments simulated in this stage of the research.

Table 5-47. Design of Experiments for Variable Sample Size

Exp.	Random Sampling		Subset Pattern		Tendency Measure Estimator	
	Simple	Systematic	Common	Individual	$\bar{x}_{1,sub}$	$\bar{x}_{1,sub,cdna}$
1	√		√		√	
2	√		√			√
3	√			√	√	
4	√			√		√
5		√	√		√	
6		√	√			√
7		√		√	√	
8		√		√		√

In spite of the experiments defined above, the most obvious comparison to be made is the one that shows the difference in the results obtained with and without the external feedback loop over the same lot of items.

Simulation results are summarized in Table 5-48 and Table 5-49. There, it seems evident that the presence of the complementary external feedback loop helps reduce the average mean shift from the nominal L_{assy}=30 mm. In the experiment 7, the best case, the mean shift was reduced by 89% from 29.9487 to 29.9939. Figure 5-39 reveals that the feedback loop neutralized the effect of the cumulative de-noised average, which did produce an additional mean shift reduction when the feed-forward loop was acting alone (experiments 2, 4, 6 and 7). Figure 5-40, however, reveals that the price to pay for using the external feedback loop is an increment from 2.1% to 2.7% in the average standard deviation.

Table 5-48. Average Mean of Assemblies' Lengths

Loop/Controller	Experiment							
	1	2	3	4	5	6	7	8
FF + FB	29.9940	29.9933	29.9931	29.9948	29.9926	29.9939	29.9942	29.9922
FF	29.9500	29.9577	29.9493	29.9595	29.9487	29.9550	29.9487	29.9578

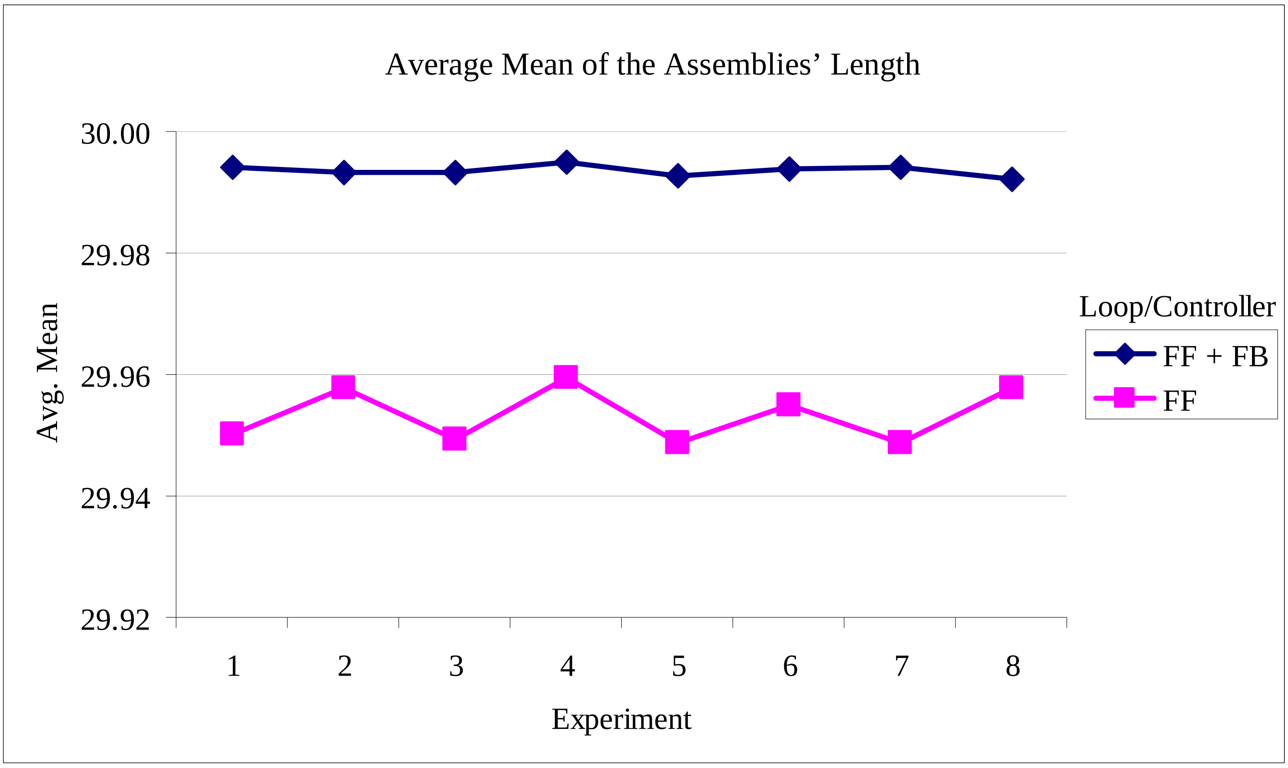


Figure 5-39. Average mean of the resulting assemblies' length.

Table 5-49. Average Std. Dev. of the Assemblies' Length

Loop/Controller	Experiment							
	1	2	3	4	5	6	7	8
FF + FB	0.2517	0.2512	0.2513	0.2527	0.2514	0.2505	0.2515	0.2503
FF	0.2452	0.2452	0.2450	0.2462	0.2446	0.2441	0.2447	0.2451

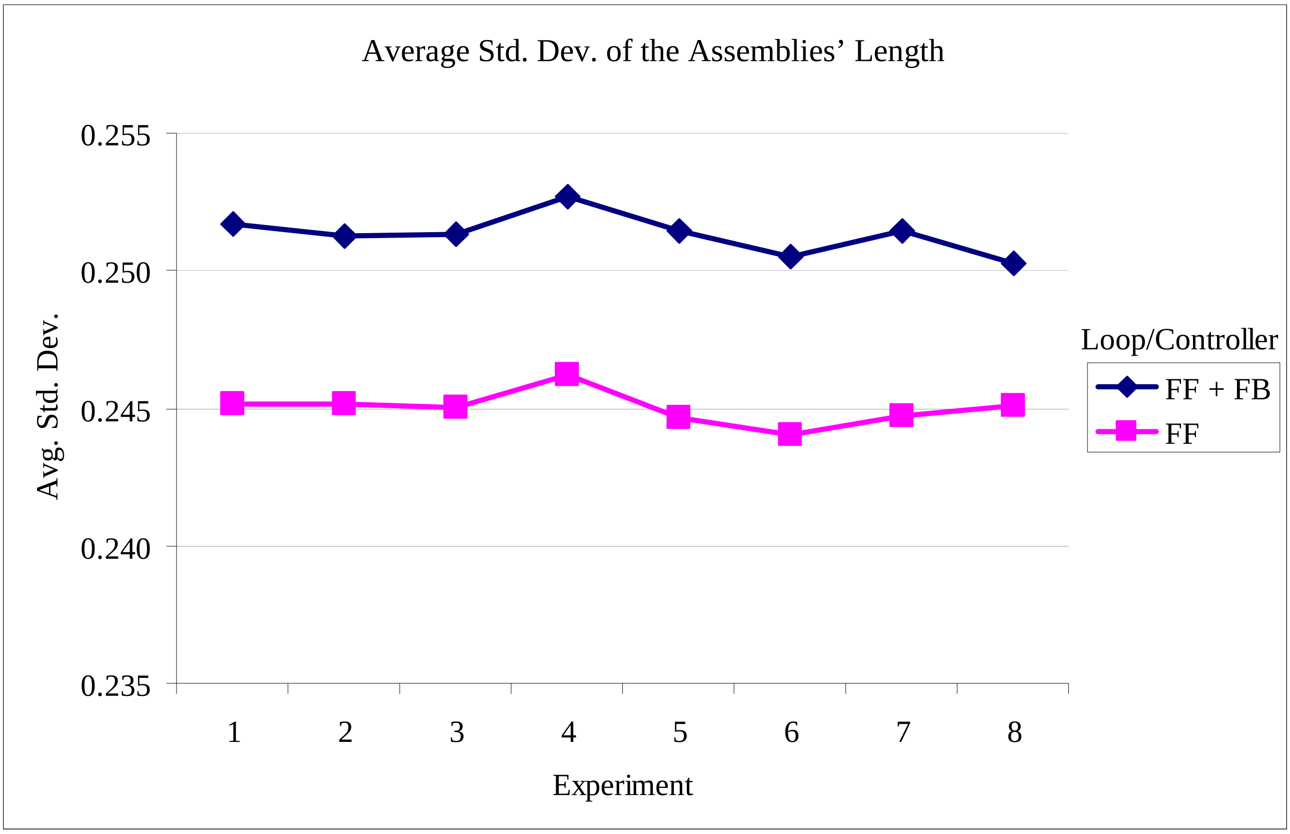


Figure 5-40. Average standard deviation of the resulting assemblies' length.

The simulations revealed that the additional feedback loop contributes also to increment the fluctuation of the mean and standard deviation values during successive replications (500 times). Table 5-50 and Table 5-51, show that in the case of the mean values, the fluctuation varied between 6% (experiment 8) and 38% (experiment 3). In the case of the standard deviation, instead, the values fluctuated between 24% (experiment 4) and 42% (experiment 1). The situation can be better visualized in Figure 5-41 and Figure 5-42.

Table 5-50. Std. Dev. of the Mean Values of the Assemblies' Length

Loop/Controller	Experiment							
	1	2	3	4	5	6	7	8
FF + FB	0.0174	0.0169	0.0168	0.0177	0.0162	0.0167	0.0170	0.0167
FF	0.0130	0.0138	0.0122	0.0150	0.0132	0.0153	0.0124	0.0158

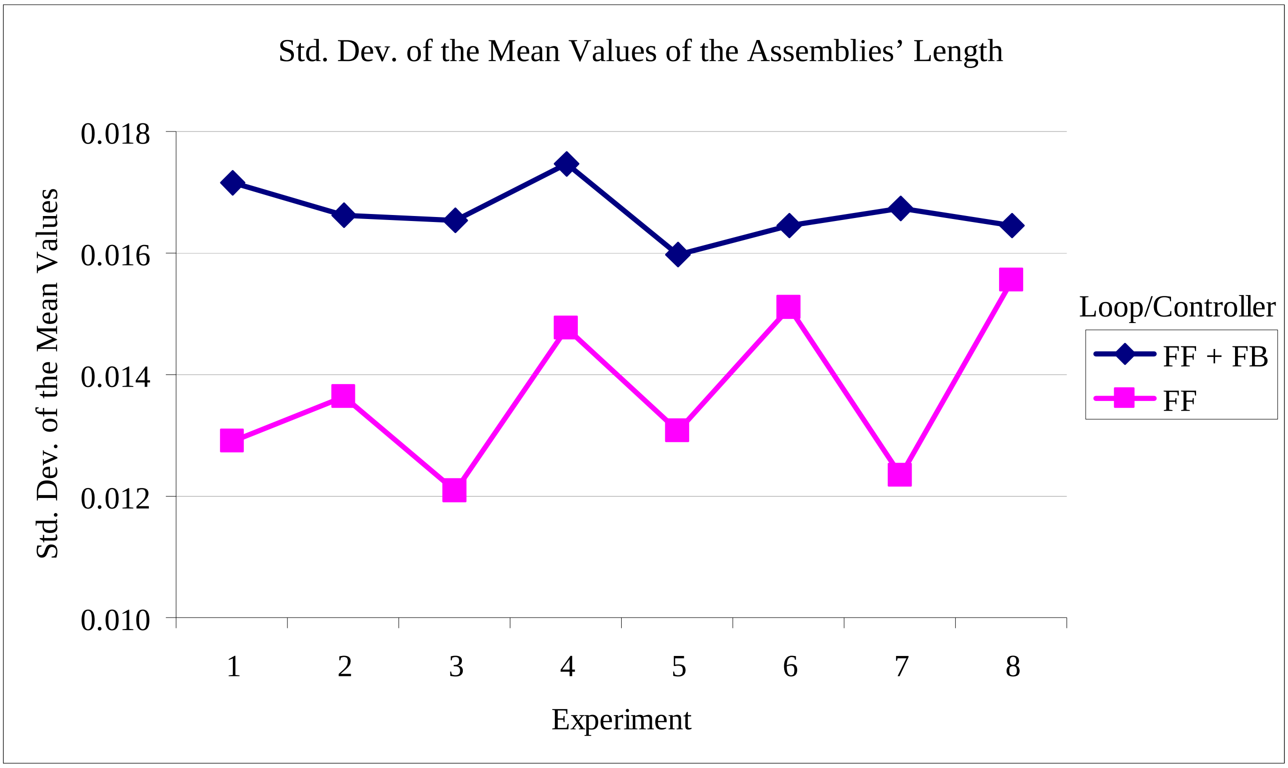


Figure 5-41. Std. Dev. of the mean values of the resulting assemblies' length.

Table 5-51. Std. Dev. of the Std. Dev. Values of the Assemblies' Length

Loop/Controller	Experiment							
	1	2	3	4	5	6	7	8
FF + FB	0.0072	0.0072	0.0072	0.0074	0.0070	0.0077	0.0070	0.0063
FF	0.0051	0.0053	0.0052	0.0060	0.0052	0.0060	0.0050	0.0047

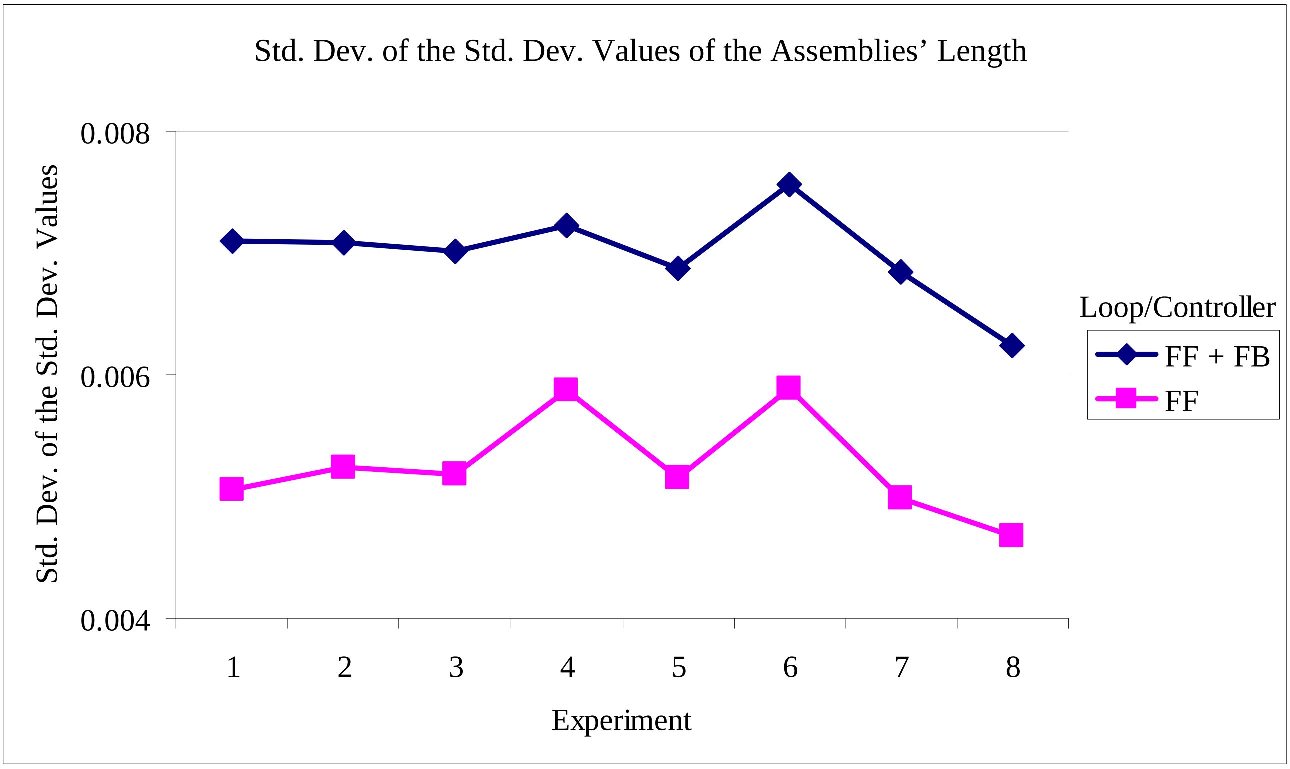


Figure 5-42. Std. Dev. of the standard deviation values of the resulting assemblies' length.

The trade-off between the benefit achieved on the shift means and the cost paid on the standard deviation has a clear impact on the process capability indices c_p and c_{pk}. While c_p decays as a consequence of the increment in the standard deviation, c_{pk} grows up influenced by the reduction of the mean shift. In particular, the fall of c_p fluctuated between 2.1% and 2.7%. The improvement of c_{pk}, instead, varied between 1% and 2%.

Table 5-52. Average Potential Capability Index c_p

Loop/Controller	Experiment							
	1	2	3	4	5	6	7	8
FF + FB	1.3244	1.3267	1.3264	1.3192	1.3257	1.3306	1.3255	1.3320
FF	1.3597	1.3595	1.3605	1.3537	1.3625	1.3658	1.3621	1.3601

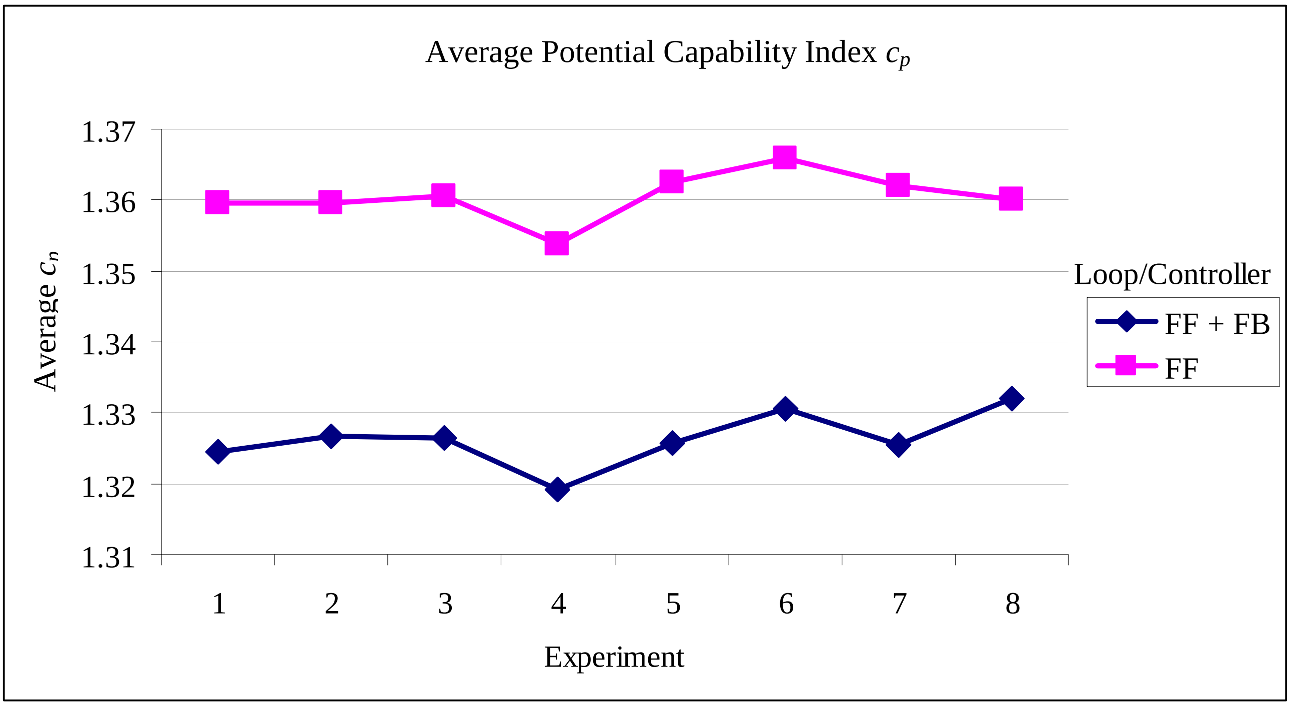


Figure 5-43. Average potential capability index c_p.

Table 5-53. Average Actual Capability Index c_p

Loop/Controller	Experiment							
	1	2	3	4	5	6	7	8
FF + FB	1.3165	1.3178	1.3173	1.3123	1.3159	1.3225	1.3179	1.3216
FF	1.2917	1.3020	1.2915	1.2989	1.2926	1.3044	1.2922	1.3027

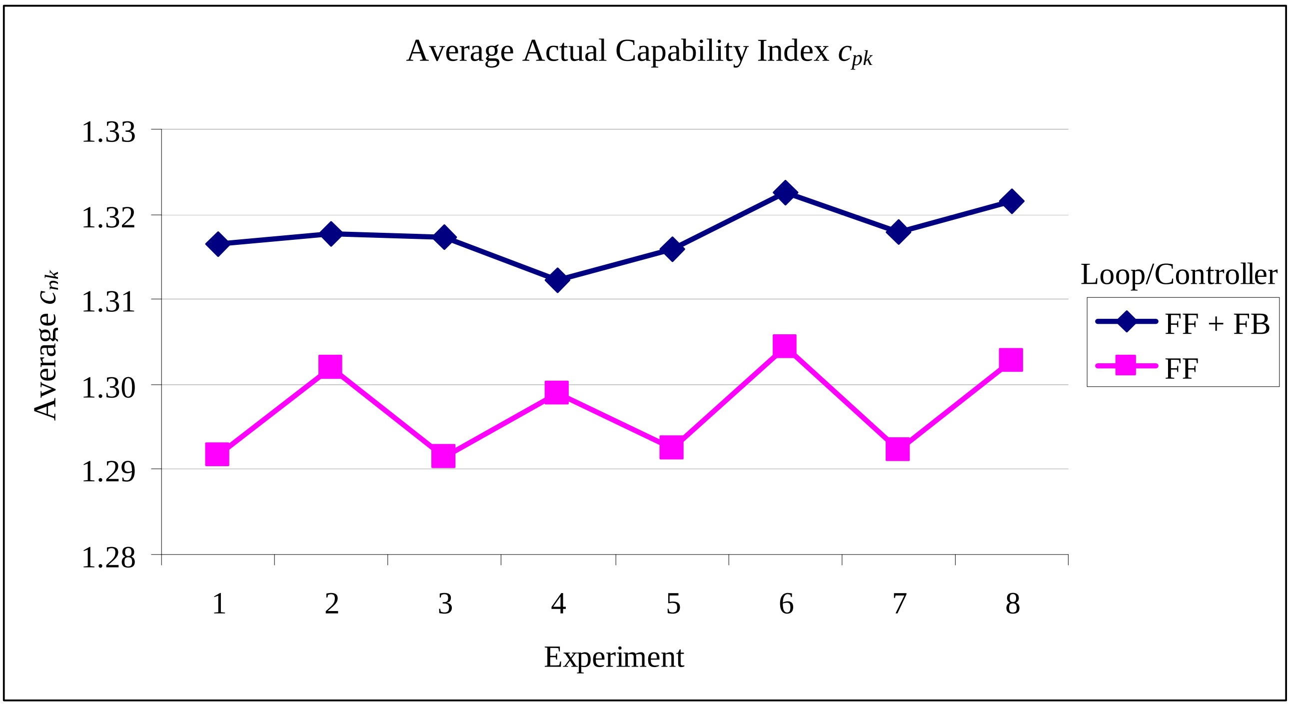


Figure 5-44. Average actual capability index c_{pk}.

It is undeniable that the additional feedback loop provided a quantifiable level of benefit which can be read either in terms of the reduction of the mean shift or in terms of the process capability indices. Nevertheless, the improvement reaches barely 2% in the case of the actual capability index.

In comparison to a fully randomized assembling, the mean shift reduction achieved by the feed-forward controller acting alone was 89% from an average mean of 29.55 to an improved value of 29.95. Whereas, the shift reduction achieve when the feed-forward and the feedback controller acted together was 98% to end up with an average mean of 29.994. This reasoning may lead to double thoughts about the properness of implementing the external feedback controller, with all the side complexities, to obtain a 9% of additional mean shift reduction but paying around 2.6% of additional standard deviation.

Finally, in the same way that a set of experiments was defined for the setup of the feed-forward controller, the feedback control may be also subject of such analysis. These experiments, however, were not covered in the present work.

5.3.9. Magnitude of the Target Adjustments

The premise of this work states that the manufacturing processes of the components to be assembled are characterized by generating items with high dimensional variation. This means that, in spite of the target adjustments, the high variation remains.

The interest in studying the magnitude of the target adjustments triggered by SFFCM resides on the fact that very small adjustments can be achieved only with high precision equipment, which would invalidate the original premise of this work.

Table 5-54 presents the values of the adjusted targets made on one of the many simulated experiments. The magnitude of the adjustment is presented in terms of the absolute value, the percentage with the respect to the nominal target, and finally in proportion to the known standard deviation σ_2 of the subprocess corresponding to the production of Component 2 and that, in this case, was equal to 0.15. The same information can be visualized in Figure 5.45.

Table 5-54. Magnitude of the Target Adjustments

Subset	Target	Adjusted Target	Adjustment		
			Abs. Value	% of Target	Times σ_2
1	10	10.55	0.55	5.55 %	3.7 σ_2
2	10	10.61	0.61	6.12 %	4.1 σ_2
3	10	10.57	0.57	5.68 %	3.8 σ_2
4	10	10.42	0.42	4.22 %	2.8 σ_2
5	10	10.34	0.34	3.45 %	2.3 σ_2
6	10	10.24	0.24	2.38 %	1.6 σ_2
7	10	10.20	0.20	1.97 %	1.3 σ_2
8	10	10.29	0.29	2.94 %	1.9 σ_2

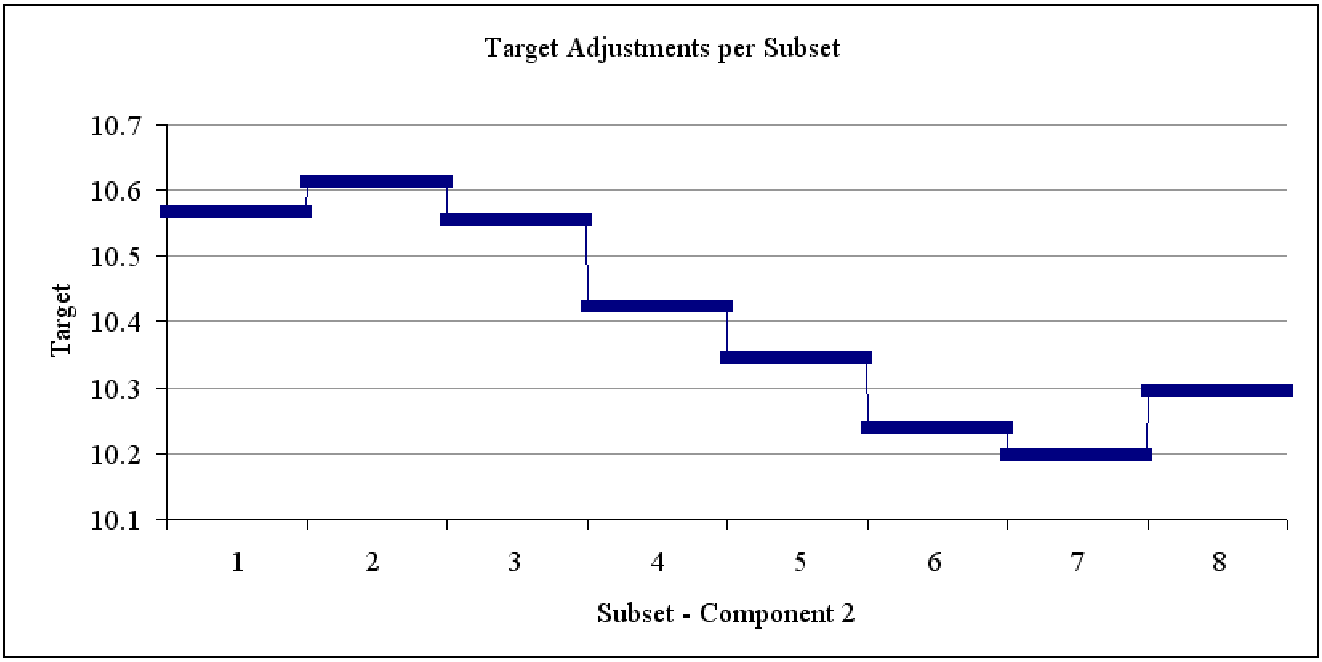


Figure 5.45. Adjusted target of the subsets of Component 2.

5.3.10. Histograms Comparison

Perhaps the best way to dimension easily the benefit of the implementation of the proposed SFFCM-based assembling technique is by means of a direct comparison between the histograms of the assemblies' lengths obtained from a fully randomized assembling and after the application of SFFCM (Figure 5.46). This plot is generated automatically by DASS after every simulation.

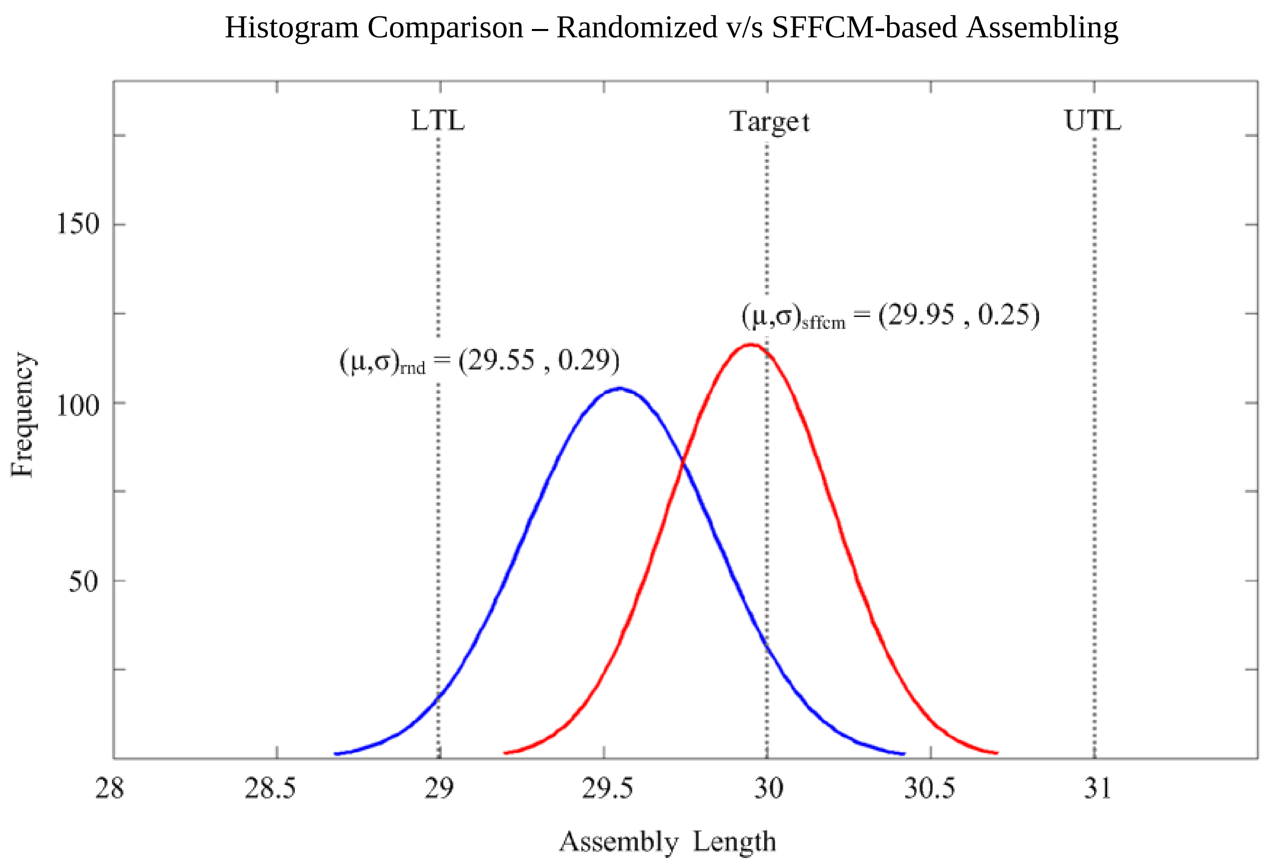


Figure 5.46. Histogram comparison between randomized and SFFCM-based assembling.

5.3.11. DASS Performance

As it was explained in section 4.2.11, DASS is equipped with an additional functionality to keep the processing performance under heavy simulation regimes. It simple executes a full data deletion and memory release after each replication. Relevant data and counters are previously saved and recovered whenever a new replication is initiated.

To carry out the simulations MATLAB Version 7.9.0.5329 (R2009b) was installed on a standard desktop PC with processor AMD Athlon II X2 250 3.01 GHz, 2 GB of RAM and MS Windows XP Pro v.2002 SP 3.

The measured performance of DASS can be visualized in Figure 5-47. There, the simulation time, expressed in seconds, of 500 consecutive replications is shown. Each dot represents the simulation a lot of 1,000 assemblies. It can be seen that, in spite of the numbers of replications, the simulation time did not experience a severe increment and maintain an average value of 23.1 seconds. Therefore, no degradation in the performance of DASS was experience during the simulations.

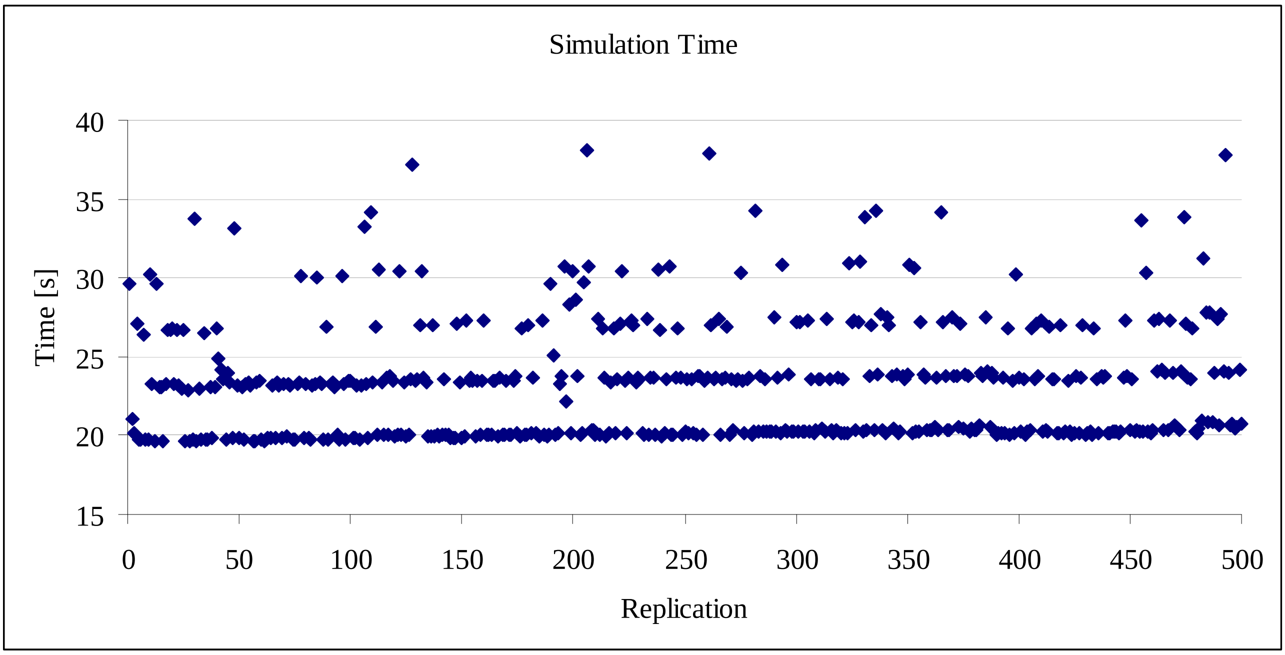


Figure 5-47. DASS performance measured in terms of the simulation time.

5.4. Chapter Summary

Through out this chapter, by means of a wide range of simulated experiments, it was shown that the performance of the proposed SFFCM-based assembling technique and its influence on the system output depend on a number of different factors. Finding the right setting for the feed-forward controller is crucial to counter effectively the controllable part of the process variation and to diminish its impact on the distribution of the resulting assemblies' length. With the help of massive simulations, the influence of different factors was quantified and expressed in terms of the average shift mean and the average standard deviation of the length of the final assemblies. Besides that, great importance was given to the ability of the controller to provide consistent results after massive experiment replications. For this reason, the analysis of the variation of the mean values and the standard deviation values was developed as well.

The first set of experiments aimed the problem of the subset size. Simulation results showed that the system output is highly influenced by the subset size. In general, the results were better when the subset size was rather small. However, small sizes imply more adjustments which are expensive in terms of resources and that should be optimized whenever it is possible. A good compromise between cost and benefits was obtained when the subset size was set to either 100 or 125, requiring 10 and 8 adjustments per lot respectively.

The second set of experiments focused on the problem of the sample size or the inspection rate. Simulation results showed that this one is also an influential factor in the system output. As expected from the theoretical recommended sample size, the results improved systematically as the inspection rate reached a 30% of the items. Beyond that percentage, no significant benefit was obtained. In general, an inspection rate between 20% and 30% delivered acceptable results.

The third group of experiments centered the attention on the estimator of the central tendency measure. Simulation results showed that the use of the proposed cumulative de-noised average, in combination with a subset size of 125 along with an inspection rate of 20%, instead of the sample mean, helped model and counter the long-term drift in a better way and thus, better results were achieved.

The fourth set of experiments focused on the influence of the inclusion of the measurement uncertainty on the proposed model. Simulation results showed that the consideration of the measurement uncertainty affected the values of the adjusted tolerances and, in consequence, the values of the capability indices of the target subprocess.

The fifth set of experiments dealt with the controller response delays. Simulation results showed that, just like other control models, the performance of the proposed SFFCM was affected by the presence of response delays in the application of the adjustments after being triggered. Simulations revealed that the effect on the average mean and on the average standard deviation of the resulting assemblies' length was proportional to the length of the delay itself.

The sixth group of experiments explored the ability of the proposed feed-forward controller to overcome the offset problem in a parallel manufacturing configuration. Simulation results showed that under certain settings the proposed controller was able to produce significant improvements on the system output. However, the results were not good enough to reach a potential capability index higher than 1.33. In the best case, when the subset size was set to 50 and the inspection rate set to 20%, c_p increased by 4.7% while c_{pk} increased by 78%.

The seventh set of experiments was designed to investigate the performance of the feed-forward controller when assembling multiple components and to quantify the influence of the position in which the controller is placed. Simulation results showed that the results improved as the position of the controller approached the end of the assembling line. Thus, leaving cost considerations aside, the optimal configuration would be the one that let the controller act on the last component of the assembling line so that no additional variation is added and the corrective actions are not lost.

The eighth and last set of experiment was designed to evaluate the influence of a complementary external feedback loop on the system output. Simulation results showed that, when the subset size was set to 125 and the inspection rate in both inspection points was set to 20%, the presence of the external feedback loop helped reduce the average mean shift by 9% in addition to the 89% obtained by the feed-forward controller acting alone. However, the feedback controller contributed to increment by 2.6% the average standard deviation that had been reduced by 14% by the feed-forward controller acting alone.

Finally, the massive replications of the simulations helped demonstrate the effectiveness of the strategy implemented to maintain the performance of DASS during heavy processing regimes.

6. CONCLUSION

6.1. Introduction

In this thesis, a novel assembling technique based on SFFCM has been developed. Taking advantage of the dynamic adjustment of specifications and the feed-forward control scheme, the new technique was conceived to help producing low variation assemblies from high variation components.

The proposed technique aims three mayor objectives: reduce the variation of the resulting assemblies, reduce the scrap levels and improve the process capability indices. To achieve them, the new technique combines adaptive and selective assembling approaches with emphasis in the optimization of the inspection task.

Different from classical approaches in which the nature of the variation is usually not considered, the Statistical Dynamic Specifications Method (SDSM) takes full advantage of the superposition of random noise and the potentially controllable long-term drift to help determine the appropriate adjustments to the target and tolerance of a given component. The Statistical Feed-Forward Control Model (SFFCM) relies on the iterative application of SDSM on small subsets of items produced consecutively in a short-time interval to apply the necessary specification adjustments and to counter the effect of the long-term drift as explained in Chapter 3.

The innovative nature of the technique proposed in this work made necessary the development of a piece of software featured with a range of specialized modules to carry out the simulation of different assembling experiments. A full description of the Dynamic Assembling Simulation Software (DASS) was given in Chapter 4.

The properness and applicability of SDSM and SFFCM introduced in Chapter 3 and implemented according to the algorithms described in Chapter 4 were finally simulated with the help of DASS. A vast number of experiments were designed, simulated and replicated so that enough data to analyze, to discuss and to draw conclusions were generated. All the experiment simulations were covered in Chapter 5.

The following sections present the research advancements achieved during the completion of this work and the areas of future research that might extend the horizons of this thesis.

6.2. Research Advancements

Through out this work many little steps, source of valuable conclusions, were progressively completed. In these sections, the most important learnt lessons, achievements and conclusions are given and classified in four groups according to the research stage they belong with.

6.2.1. Adaptive and Selective Assembling

The analysis of the existing assembling techniques for high variation components presented in Chapter 2 revealed several downsides that deserved special attention.

A mayor drawback found in the selective techniques is the need of full inspection, i.e. 100%, which may not be realizable in many manufacturing processes. Besides that, additional resources have to be allocated for managing both tolerance groups and inventories, and for overproducing items if the binning strategy requires it.

Adaptive techniques have limitations too. The use of an estimator without "memory" like the sample mean implies that only the data retrieved from the last inspected sample is really taken into account to calculate the necessary adjustments. Besides that, in some cases, adaptive techniques require additional machining of individual items.

A common characteristic of the discussed assembling techniques is that neither the selective nor the adaptive approach considers the dynamic nature of the variation as a function of time and as the result of the superposition of random noise and a potentially controllable long-term drift.

In conclusion, the downsides found in the existing assembling techniques can be used to develop a different technique that combines the advantages of the selective and the adaptive approaches. The objectives of this new technique can be formulated as follows:

1. reduce the dimensional variation of the resulting assemblies,
2. reduce the scrap of inner component items and resulting assemblies,
3. improve the process capability indices,
4. optimize the inspection effort,
5. consider the dynamic nature of the variation to counter the presence of a long-term drift.

6.2.2. SFFCM-based Assembling

Several achievements can be mentioned and many conclusions can be derived from the novel assembling technique presented in Chapter 3. Two fundamental concepts were then introduced: Statistical Dynamic Specifications Method (SDSM) and Statistical Feed-Forward Control Model (SFFCM).

SDSM was conceived as a powerful tool to help determine the correct specification adjustments for the target and the tolerance of the component of an assembly. Following the notation given for the two-component assembly used as example through this work, SDSM acts over small subsets of items of Component 1 produced consecutively in a short-time interval from which a sample is drawn for inspection. The sample mean $\bar{x}_{1,sub(i)}$ and the standard deviation $s_{1,sub(i)}$ found in the subset *i* are then considered to determine the adjusted specifications of the matching subset *i* of Component 2 using the estimators of $\hat{L}_{2,adj,sub(i)}$ and $\hat{t}_{2,adj,sub(i)}$ (equations 3-46 and 3-43).

In order not to use only the data coming from the last inspected subset but to take full advantage of the data gathered during previous samplings, SDSM has been equipped with an estimator “with memory” as an alternative to the classic sample mean: the Cumulative De-Noised Average (CDNA) $\bar{x}_{cdna}$. Besides that, SDSM can include the measurement uncertainty in the model. In this case, the adjusted tolerance of the matching subset *i* of Component 2 is determined with the estimator $\hat{t}_{2,adj,sub(i),unc}$ (equation 3-56).

The immediate consequence of applying SDSM on the items of the subset *i* of Component 2 is an extended tolerance, determined using $\hat{t}_{2,adj,sub(i)}$ (equation 3-43), and therefore a lower scrap level and higher capability indices. Besides that, the mean shift found on the assemblies resulting from mating the subsets *i* of Component 1 and Component 2 is expected to be lower due to the adjusted target, which can be determined using $\hat{L}_{2,adj,sub(i)}$ (equation 3-46).

In conclusion, by means of considering small group of items produced consecutively in a short-time interval, SDSM could make possible:

1. to optimize the inspection effort by drawing a sample instead of performing a full inspection to estimate the mean $\mu_{1,sub(i)}$ and standard deviation $\sigma_{1,sub(i)}$ of a given subset *i*, by means of using the estimators $\bar{x}_{1,sub(i)}$ and $s_{1,sub(i)}$,
2. to determine the band $\mu_{1,sub(i)} \pm 3\sigma_{1,sub(i)}$ in which 99.73% of the items of a given subset *i* of Component 1 are supposed to fall. The estimate value can be determined using the sample mean and the sample standard deviation $\bar{x}_{1,sub(i)} \pm 3s_{1,sub(i)}$,
3. to determine the adjusted target and tolerance of the matching subset *i* of Component 2 using the estimators $\hat{L}_{2,adj,sub(i)}$ and $\hat{t}_{2,adj,sub(i)}$ respectively (equations 3-46 and 3-43) ,
4. to improve the capability indices, potential and actual, of the manufacturing process of Component 2 as a consequence of the extended tolerance $t_{2,adj,sub(i)}$ (equation 3-39). Estimate values of the indices of a given subset *i* can be determined using the estimators of $\hat{c}_{p,2,adj,sub(i)}$ and $\hat{c}_{pk,2,adj,sub(i)}$ respectively (equations 3-44 and 3-45).

SFFCM was thought as an innovative monitoring tool that exerts the control over a system or process by means of applying SDSM repeatedly as many times as needed until the production lot is completed. This action contributes to counter the presence of a detectable long-term drift in the variation thanks to the compensation effect produced by the floating target of the subsets of Component 2. Since the assembling is carried out using subsets of Component 1 and Component 2 that are complementary with each other, the resulting lot of assemblies is expected to have a lower variation and a reduced mean shift.

The flexibility of SFFCM facilitates its application in different schemes and configurations. For example, it can be used even in parallel manufacturing lines where the offset problem is present. To do it, SFFCM has been equipped with three prediction algorithms to help overcome the offset problem.

Since the fundamental idea behind SFFCM is the separation of the system under study in two subsystems, a feeding and a controlled one, the model lends itself for multi-component assembling tasks. The strategy is rather simple and consists in reducing the problem to the assembling two subassemblies that play the role of the feeding and the controlled subsystems.

A radically different configuration adopted by the SFFCM is the inclusion of a external feedback loop to monitor the system output and to feed the system back, complementing in this way the data provided by the feed-forward controller. Thus, the target adjustments can be computed taking these two sources of information into account.

In conclusion, the implementation of SFFCM could make possible:

1. to known the pattern described by the long-term drift detected in the variation of the items of Component 1 and that is revealed by the central tendency measure, either $\bar{x}_{1,sub(i)}$ or $\bar{x}_{1,sub(i),cdna}$, of each subset *i*,
2. to reduce the variation and the mean shift of the length of the resulting assemblies, and therefore, to reduce the scrap level at the assembly side and to improve the assembly process capability indices $c_{p,assy,adj}$ and $c_{pk,assy,adj}$ (equations 3-24 and 3-25),
3. to overcome the offset problem of parallel manufacturing lines. In this case the sample mean $\bar{x}_{1,sub(i)}$ and the sample standard deviation $s_{1,sub(i)}$ of the subset *i* of Component 1 are employed to determine, by means of the prediction algorithms, the adjusted specifications for the subset *(i+1)* of Component 2 and that can be computed using the estimators $\hat{L}_{2,adj,sub(i+1),pred}$ and $\hat{t}_{2,adj,sub(i+1),pred}$ (equations 3-58 and 3-59),
4. to deal with multi-component assembling problems by means of reducing the situation to the mating of two subassemblies that will represent the usual feeding and the controlled subsystems,
5. to feed the system back with data gathered from the system output. Specifically, the sample mean $\bar{x}_{assy,sub(i)}$ of the assemblies resulting from mating the subsets *i* can be used to help calculate the target a posterior subset *(i+1)* of Component 2. This, in complement to the sample mean $\bar{x}_{1,sub(i)}$ retrieved from the subset *(i+1)* of Component 1.

6.2.3. Dynamic Assembling Simulation Software (DASS)

Some of the most attractive functionalities of DASS, from the SFFCM standpoint, were presented with great detail in Chapter 4.

DASS was developed with the only intention of making possible the simulation of experiments to evaluate the properness of the proposed SFFCM-based assembling technique in different conditions. DASS was conceived to offer the experimenter full flexibility to define the simulation environment. To do it, several setting files are available to be completely parameterized.

Among others, the experimenter is allowed to define:

1. the number of components to be assembled,
2. the position k of the component whose target and tolerance is meant to be adjusted,
3. the characteristics (trends, oscillations, steps, slope, frequency, amplitude and noise) of the combined variation acting over the process,
4. the subset size,
5. the sampling strategy and the inspection rate,
6. the sample estimators (sample mean, CDNA, sample standard deviation),
7. the value of the measurement uncertainty,
8. the presence of the offset problem in parallel lines and the prediction modes,
9. the magnitude of the response delays, etc.

In conclusion, the development of DASS made possible:

1. to simulate a wide range of experiments that helped quantify the influence of specific or combined factors on the system output,
2. to introduce different types of variation effects to alter the component lots keeping the characteristic parameters, μ and σ, of the corresponding probability density functions (PDF) unaltered,
3. to plot a range of different graphics, comparison charts, normality tests and 2D and 3D diagrams,
4. to set different experiments up in the configuration files so that they can be sequentially simulated altogether to facilitate their comparison,
5. to determine the position k of the component to be adjusted that maximizes the effectiveness of SFFCM in a multi-component assembly,
6. to maintain the software performance during massive experiment replications by means of implementing an strategy that optimizes the processing and the memory resources.

6.2.4. Simulation

A comprehensive description of the simulation results was given in Chapter 5. There, plenty of tables, graphs, and explanations are provided to help the reader understand and visualize how small changes in the parameters or configurations might affect the effectiveness of the proposed assembling technique.

The effectiveness of SFFCM was measured in terms of the reduction achieved in the mean shift ($\mu_{assy,adj}$- L_{assy}) and the standard deviation $\sigma_{assy,adj}$ of the length of the resulting assemblies with respect to the nominal target L_{assy}, and in terms of the reduction of the scrap levels and the improvement of the process capability indices $c_{p,assy,adj}$ and $c_{pk,assy,adj}$.

In conclusion, the simulation of the experiments with the variation pattern unaltered, made possible:

1. to show that the system output is highly sensitive to the subset size. In general, the results were better when the subset size was set to either 100 or 125, i.e., when 10 or 8 adjustments were executed to complete a lot of 1,000 assemblies,
2. to prove that an inspection rate between 20% and 30% will delivered acceptable results. Higher inspection rates did not bring additional benefits,
3. to show the suitability of the proposed cumulative de-noised average $\bar{x}_{1,cdna,sub(i)}$ instead of the sample mean $\bar{x}_{1,sub(i)}$ for modeling the long-term drift. Particularly, in combination with a subset size of 125 and an inspection rate of 20%,
4. to prove that the performance of SFFCM is affected by the presence of response delays in the application of the adjustments after being triggered and that the loss of performance is proportional to the length of the delays,
5. to show that, compared to a randomized assembling, in presence of an offset in a parallel configuration and setting the subset size to 50 and the inspection rate to 20%, SFFCM was able to improve $c_{p,assy,adj}$ by 4.7% and $c_{pk,assy,adj}$ by 78%. These numbers, however, were not good enough to reach a $c_{p,assy,adj}$ higher than 1.33,
6. to show that when assembling multiple components whose manufacturing processes are characterized by similar high levels variation, the best choice is to let the controller act on the last component of the assembling line so that no addition variation is stacked and the corrective actions are not lost,
7. to show that the inclusion of a complementary external feedback loop to monitor the system output, when setting the subset size to 125 and inspection rate to 20%, helped reduce the average mean shift by 9% in addition to the 89% obtained by the feed-forward controller acting alone. However, the feedback loop also contributed to increment by 2.6% the average standard deviation which had been previously reduced by 14% by the feed-forward controller acting alone,
8. to probe that the proposed SFFCM-based assembling does not require necessarily high precision equipment to be implemented since the magnitude of the required adjustments fluctuated between 2% and 6% of the original value of the nominal target.

In comparison to a full randomized assembling, the benefits achieved by implementing a SFFCM-based assembling, setting the subset size to 125 and the inspection rate to 20%, were:

1. an average reduction by 89% of the mean shift. From an assembly mean μ_{assy} equal to 29.55 to an adjusted assembly mean $\mu_{assy,adj}$ equal to 29.95. The assembly nominal target L_{assy} was originally set to 30.00 mm.
2. an average reduction by 14% of the assembly standard deviation. From an assembly standard deviation σ_{assy} equal to 0.29 to an adjusted assembly standard deviation $\sigma_{assy,adj}$ equal to 0.25.
3. an average improvement of the potential capability index by 16%. From an original $c_{p,assy}$ equal to 1.15 to an adjusted $c_{p,assy,adj}$ equal to 1.34.
4. an average improvement of the actual capability index by 101%. From an original $c_{pk,assy}$ equal to 0.63 to an adjusted $c_{pk,assy,adj}$ equal to 1.27.
5. an average reduction by 100% of the assembly items out of tolerance from a original value of 28.6 per thousand opportunities to zero.

Finally, based on the numbers above it can be concluded that by means of applying the proposed SFFCM-based assembling it is possible to end up with products having low dimensional variation made of components characterized by high dimensional variation. In other words, it is possible to obtain a capable process (c_p>1.33) from the combination of non-capable subprocesses.

The simulations showed that the proposed SFFMC-based technique, a combination of adaptive and selective approaches with emphasis in the inspection optimization, effectively helped achieve the initial objectives of this thesis: reduce the process variation, reduce the scrap level and improve the process capability indices.

6.3. Future Research

The flexibility of the proposed SFFCM-based assembling technique and the promising simulation results obtained with DASS wet the appetite for exploring new applications for this technique.

6.3.1. Not Normal Distributions

The data obtained from manufacturing processes are often considered to be normally distributed. In fact, in many cases this assumption is true. As a consequence, most of the existing simulation tools were developed to manipulate only normally distributed data. DASS is not an exemption to this practice and for this reason it might result interesting to implement new features. The possibility of simulating processes that give to rise not normally distributed data would give DASS an additional flexibility that could multiply its applicability.

6.3.2. Multi-Dimensional Problem

Through out this work, the discussion was reduced to a one-dimensional problem. Although the analysis of the two-dimensional (2D) or the three-dimensional (3D) problem would not differ substantially from the analysis developed here, there will be plenty of additional considerations to take into account. For example, the order in which dimensions should be adjusted according to certain criteria, etc.

6.3.3. Variable Subset Size and Inspection Rate

SFFCM considers the subset size and the inspection rate as fixed parameters thought out the production cycle. Nevertheless, there is no reason not to explore a different approach that might help optimize even more the inspection task.

One alternative is the construction of statistical models using the data retrieved from previously inspected subsets to predict the variation of coming subsets. If no drift is predicted then the following subset size could be enlarged or shortened if the drift has a pronounced slope. Similar approach may be applied to the standard variation.

Another possible approach is to concentrate the inspections at the beginning of each subset and then, according to the measured sample standard deviation, decide if it is necessary to increase or decrease the inspection rate in that subset.

6.3.4. Prediction Modes for Parallel Production Lines

The prediction modes proposed to overcome the offset problem in parallel configurations demonstrated not to be good enough for the challenge. In fact, the proposed models, based on a robust regression algorithm and on the construction of polynomials of second degree, performed even worse than prediction algorithm based on the repetition of the last adjustments. More sophisticated models could be constructed to deal with situations like that.

6.3.5. Cost Considerations

The Statistical Dynamic Specifications Method (SDSM) proposed in this thesis, does not consider any cost analysis to define the estimators $\hat{L}_{i,adj,sub(j)}$ and $\hat{t}_{i,adj,sub(j)}$ that are used to determine the specification adjustments. More sophisticated models could eventually take into account the costs of the adjustments. For example, the cost of additional material if the target is enlarged, the cost of additional machine movements, etc.

6.3.6. Open Source Development Environment for DASS 2.0

Even though MATLAB offered many advantages to develop simulation software for heavy numerical processing, licensing is still a big obstacle and even bigger, when specific tool-boxes are needed. A possible alternative is the open source development environment R which also offers powerful capabilities to manipulate vectors and it is available for free. Environments like R should be kept in mind if a second version of DASS is some day to be developed.

6.4. Chapter Summary

In the first section, a short review of the motivation for developing an innovative assembling technique based on SFFCM is given. The three mayor goals (reduce process variation, reduce scrap level and improve capability indices) and the differences with classical approaches that do not consider the dynamic nature of the variability are mentioned too.

In the middle section, a comprehensive list of the advancements made in each stage of the research is presented. According to the structure of this work, first the advancements and conclusions corresponding to the existing assembling techniques were given. The same was made with the proposed SFFCM-based assembling technique, with the structure of DASS and finally, the advancements and conclusions made during the simulation stage were presented as well.

In the last part of this chapter, some of the possible alternatives to continue this line of research are presented. Among them: the study of processes that generate not normally distributed data, the analysis of the multi-dimensional problem, the implementation of variable subset sizes and variable inspection rates, the improvement of the proposed prediction modes to overcome the offset problem, the inclusion of costs considerations in SDSM and at the end, the replacement of MATLAB by a free open source development environment.

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APPENDICES

APPENDIX A. MATLAB BUILT-IN FUNCTIONS

A.1 Automatic One-Dimensional De-Noising: Function *wden*

The built-in function *wden* performs an automatic de-noising process of a one-dimensional signal using wavelets. It returns a de-noised version *XD* of input vector *X* obtained by thresholding the wavelet coefficients [MATLAB]. It can be coded using the following syntax

[XD , CXD , LXD] = wden (X , TPTR , SORH , SCAL , N , '*wname*')

where *XD* is the de-noised version of *X* and CXD and LXD are the wavelet decomposition structure of the de-noised signal XD.

TPTR string contains the threshold selection rule:
- 'rigrsure' uses the principle of Stein's Unbiased Risk.
- 'heursure' is an heuristic variant of the first option.
- 'sqtwolog' for universal threshold $\sqrt{2\ln(\circ)}$
- 'minimaxi' for minimax thresholding

SORH ('s' or 'h') is for soft or hard thresholding

SCAL defines multiplicative threshold rescaling:
- 'one' for no rescaling
- 'sln' for rescaling using a single estimation of level noise based on first-level coefficients
- 'mln' for rescaling done using level-dependent estimation of level noise

The wavelet decomposition is performed at level N and '*wname*' is a string containing the name of the desired orthogonal wavelet. There are four output wavelet filters

- the decomposition low-pass filter
- the decomposition high-pass filter
- the reconstruction low-pass filter
- the reconstruction high-pass filter

Table A-1. Wavelet Families

Families	Wavelets
Daubechies	'db1' or 'haar', 'db2', ... ,'db10', ... , 'db45'
Coiflets	'coif1', ... , 'coif5'
Symlets	'sym2', ... , 'sym8', ... ,'sym45'
Discrete Meyer	'dmey'
Biorthogonal	'bior1.1', 'bior1.3', 'bior1.5'
	'bior2.2', 'bior2.4', 'bior2.6', 'bior2.8'
	'bior3.1', 'bior3.3', 'bior3.5', 'bior3.7'
	'bior3.9', 'bior4.4', 'bior5.5', 'bior6.8'
Reverse Biorthogonal	'rbio1.1', 'rbio1.3', 'rbio1.5'
	'rbio2.2', 'rbio2.4', 'rbio2.6', 'rbio2.8'
	'rbio3.1', 'rbio3.3', 'rbio3.5', 'rbio3.7'
	'rbio3.9', 'rbio4.4', 'rbio5.5', 'rbio6.8'

The underlying model for the noisy signal has the following form:

$$s(n) = f(n) + \sigma e(n) \qquad \text{(A-1)}$$

where time *n* is equally spaced. The de-noising objective is to suppress the noise part of the signal *s* and to recover *f*.

In the simplest model $e(n)$ is supposed to be a Gaussian white noise $N(0,1)$ and the noise level is equal to 1. The de-noising procedure proceeds in three steps:

1. **Decomposition**. Choose a wavelet and choose a level N. Compute the wavelet decomposition of the signal s at level N.
2. **Detail coefficients thresholding**. For each level from 1 to N, select a threshold and apply soft thresholding to the detail coefficients.
3. **Reconstruction**. Compute the wavelet reconstruction based on the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N.

In the simulations, the de-noising algorithm was applied independently to each subset as soon as the data coming from the last inspected subset were retrieved (Figure A-1).

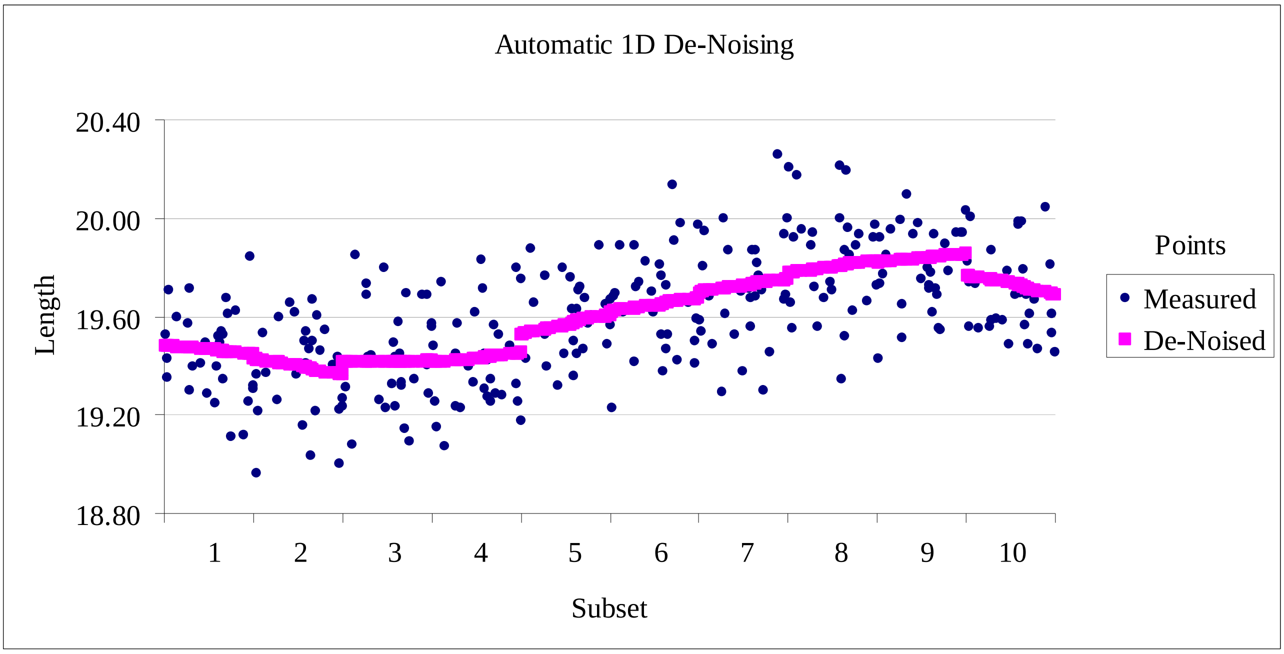

Figure A-1. Automatic de-noising in one dimension.

An example of the computation of the cumulative de-noised average $\bar{x}_{cdna}$ is presented in Figure A-2. In this case, the subset size was set to 100 and the sampling rate to 30%.

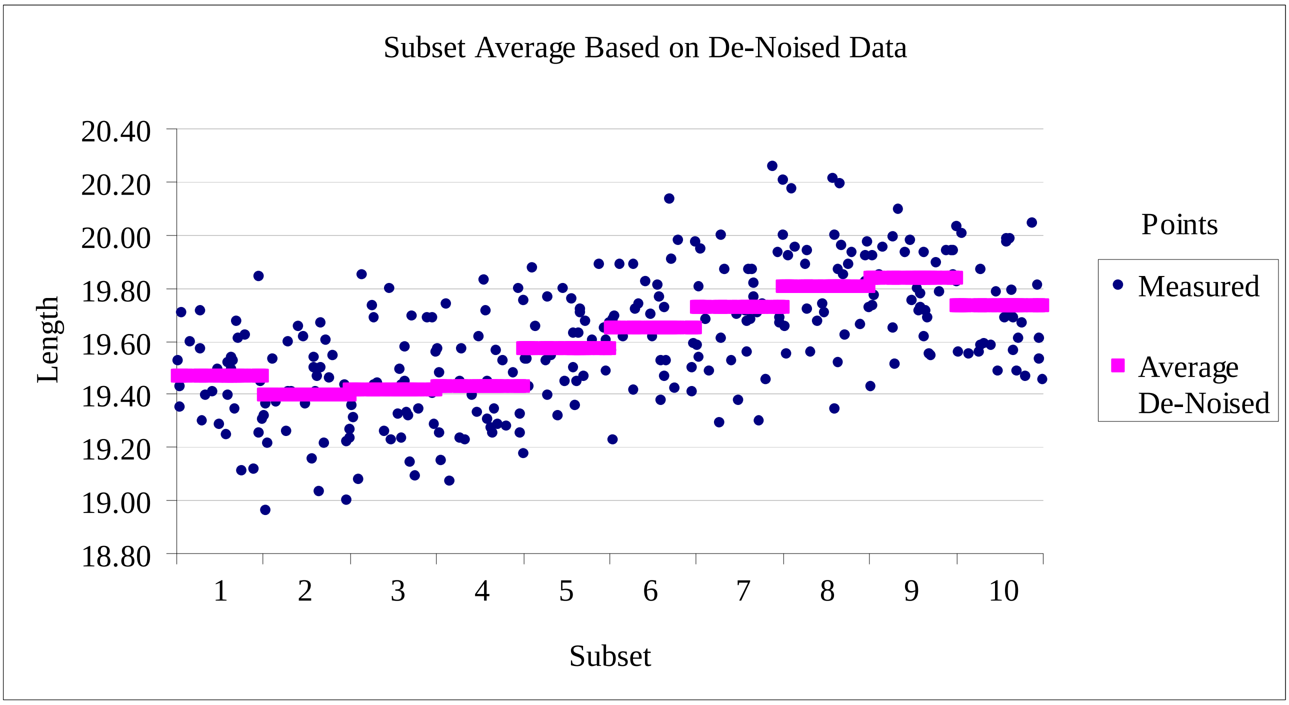

Figure A-2. Averaged de-noised data per subset.

A.2 Robust Linear Regression Fitting: Function *robustfit*

The built-in function *robustfit* returns a vector of coefficient estimates for a robust multi-linear regression. In the simulations corresponding to the prediction modes, the fitting algorithm was applied right after the data coming from the last inspected subset were de-noised. To compute the coefficients, de-noised data from all the previously inspected subsets were used. The resulting model was used then to predict the average value of the next subset. In Table A-2 both the coefficient estimates and the predicted average values shown. These numbers were obtained setting the subset size to 100 and the sampling rate to 30%.

Table A-2. Coefficients Obtained Applying *robustfit*

Subsets	Robust Linear Regression: a x + b		Predicted Average
from 1 to i	a (x 10^{-4})	B	Subset (i+1)
1	-0.1530	19.5491	19.3188
2	-7.1523	19.5026	19.3234
3	-1.0814	19.4502	19.4123
4	1.6440	19.4137	19.4878
5	1.2659	19.4167	19.4864
6	4.0193	19.3629	19.6243
7	5.6141	19.3260	19.7473
8	6.4178	19.3056	19.8515
9	6.1777	19.3124	19.8996

The algorithm is rather simple. Basically, all or some of the de-noised data available are used to construct a polynomial using a robust linear regression algorithm. Once the coefficients have been computed, the polynomial is used to project the values that would be found in the following subset *(i+1)*. This new set of data is considered then to determine the mean of the next subset, which is shown in the last column of Table A-2.

The resulting curves and their projections over the following subset *(i+1)* are plotted in Figure A-3 and Figure A-4.

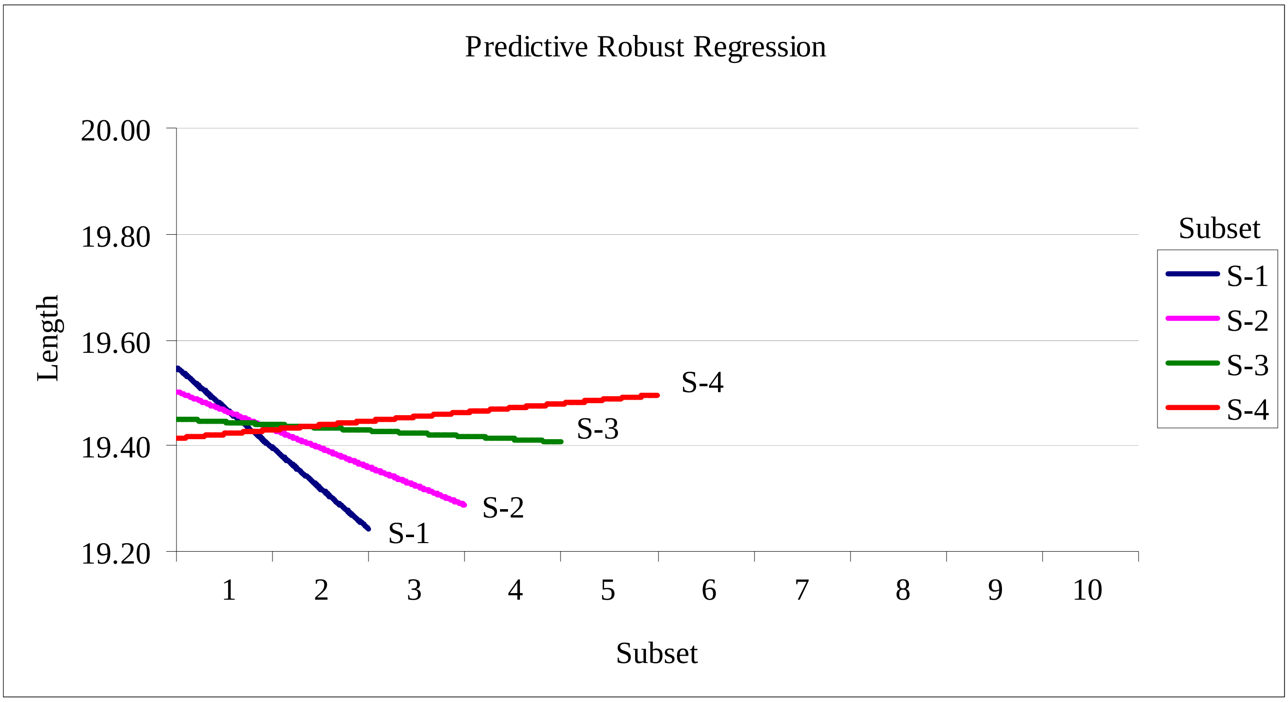

Figure A-3. Robust linear regression – Subsets 1 to 4.

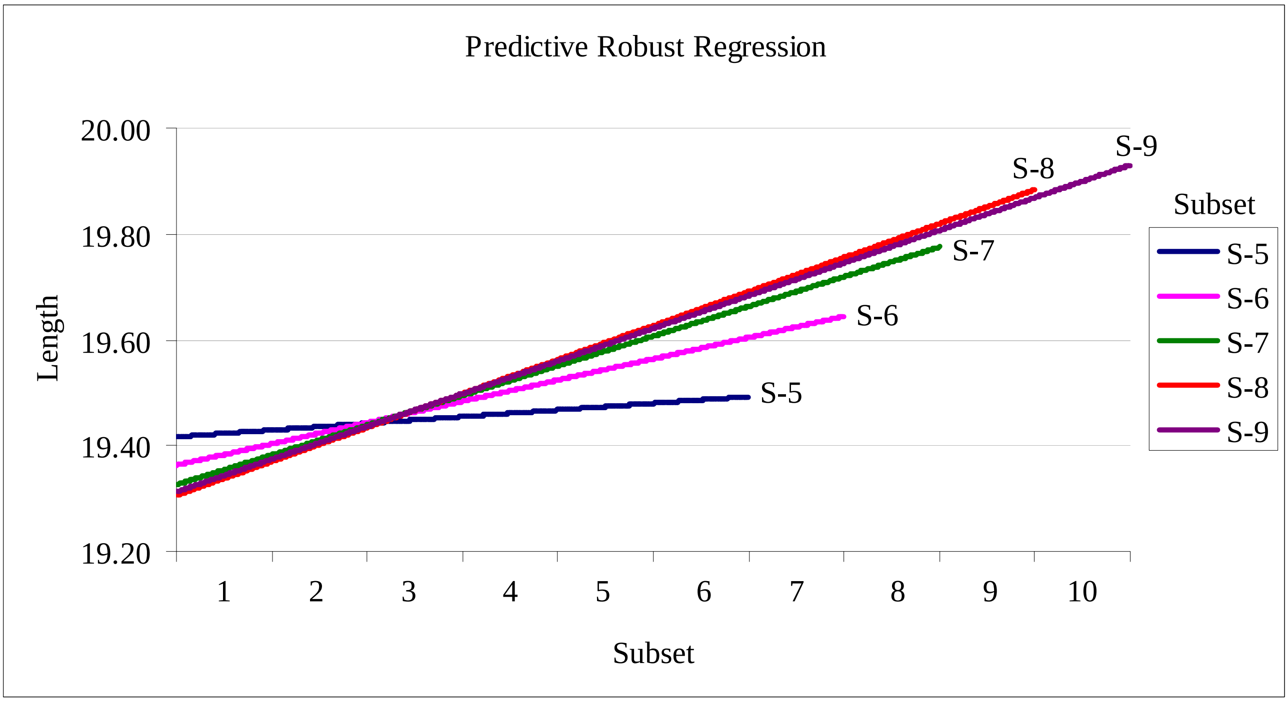

Figure A-4. Robust linear regression – Subsets 5 to 9.

The corresponding average values of the projected subset *(i+1)* are shown in Figure A-5.

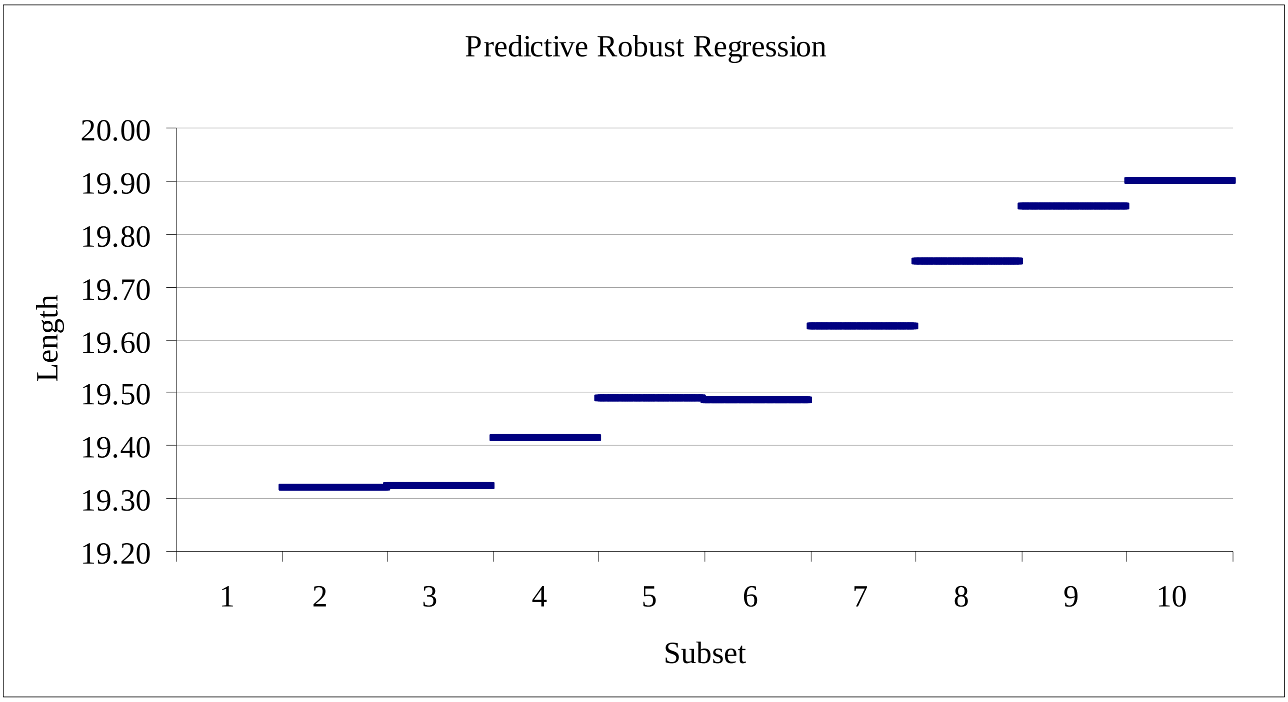

Figure A-5. Robust linear regression – Predicted subset average values.

A.3 Polynomial-Based Fitting: Function *polyfit*

The built-in function *polyfit* finds the coefficients of a polynomial of degree *n* that fits the available data in a least squares sense. In this work only polynomials of 2^{nd} degree were constructed. The fitting algorithm was applied right after the data coming from the last inspected subsets were de-noised.

Table A-3. Coefficients Obtained Applying *polyfit*

Subsets from 1 to i	2^{nd} Degree Polynomial : $a\,x^2 + b\,x + c$			Predicted Average Subset (i+1)
	a ($\times 10^{-6}$)	b ($\times 10^{-4}$)	c	
1	-1.2644	-3.9229	19.4593	19.3706
2	941.4846	-3.1247	19.4540	19.3817
3	84.7351	-4.2951	19.4568	19.4111
4	1.1599	-5.0919	19.4600	19.4670
5	2.4766	-9.5604	19.4839	19.7102
6	2.1132	-7.9363	19.4725	19.8522
7	1.4095	-4.2876	19.4428	19.9162
8	96.6185	-1.6284	19.4179	19.9791
9	43.748	1.9544	19.3799	19.9613

The coefficients were computed using de-noised data from all previously inspected subsets. The numbers shown in Table A-3 were obtained setting the subset size to 100 and the sampling rate to 30%. The resulting curves and their projections over the following subset *(i+1)* are plotted in Figure A-6 and Figure A-7.

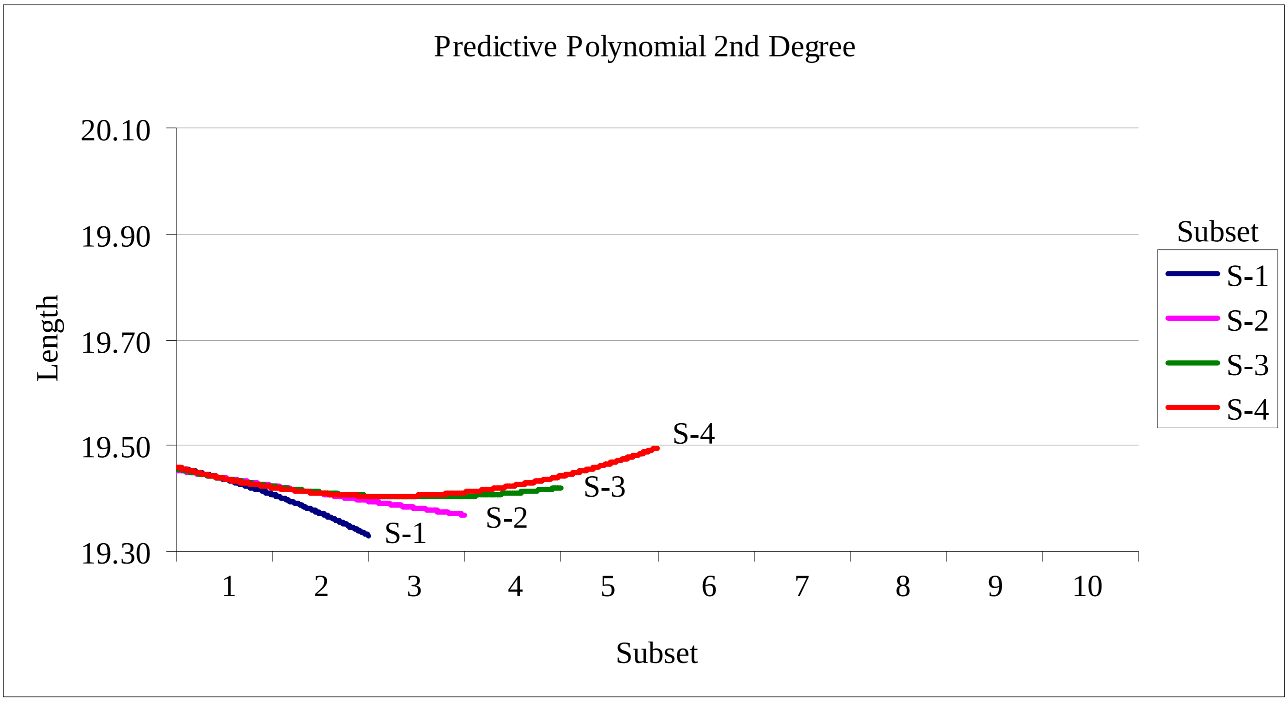

Figure A-6. Polynomial of 2nd degree – Subset 1 to 4.

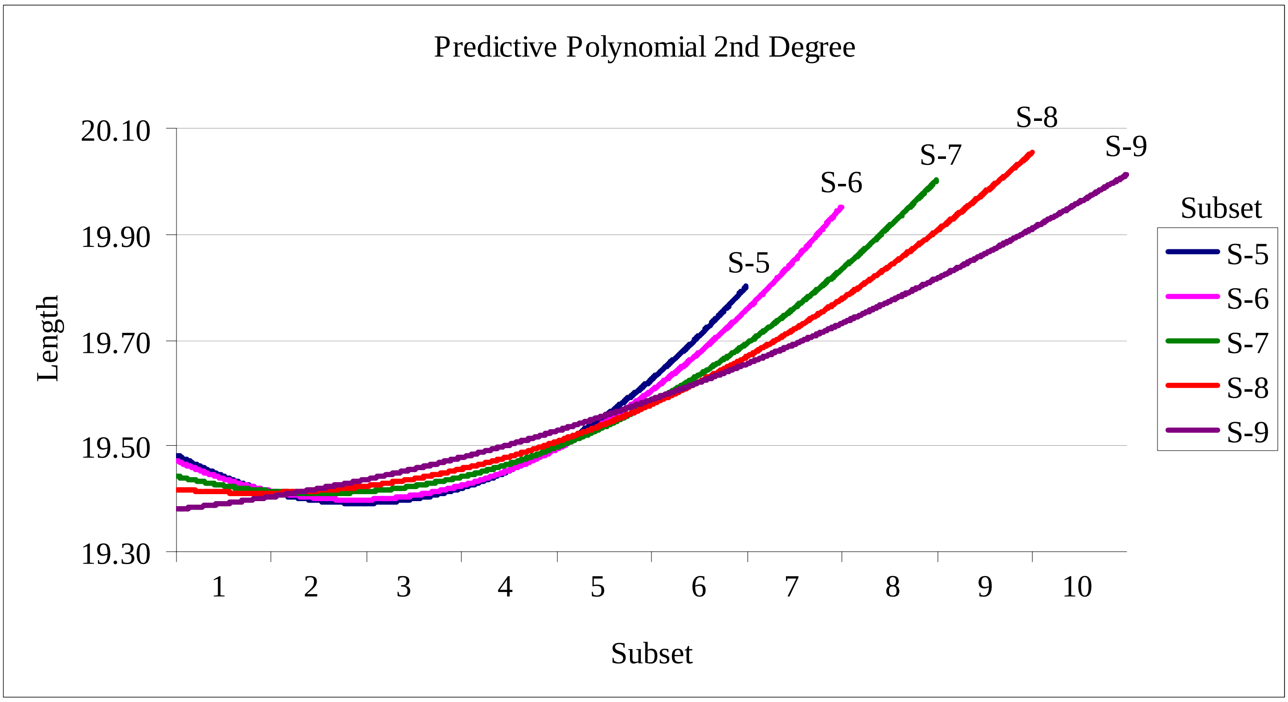

Figure A-7. Polynomial of 2nd degree – Subset 5 to 9.

The corresponding average values of the projected subsets *(i+1)* are shown in Figure A-8.

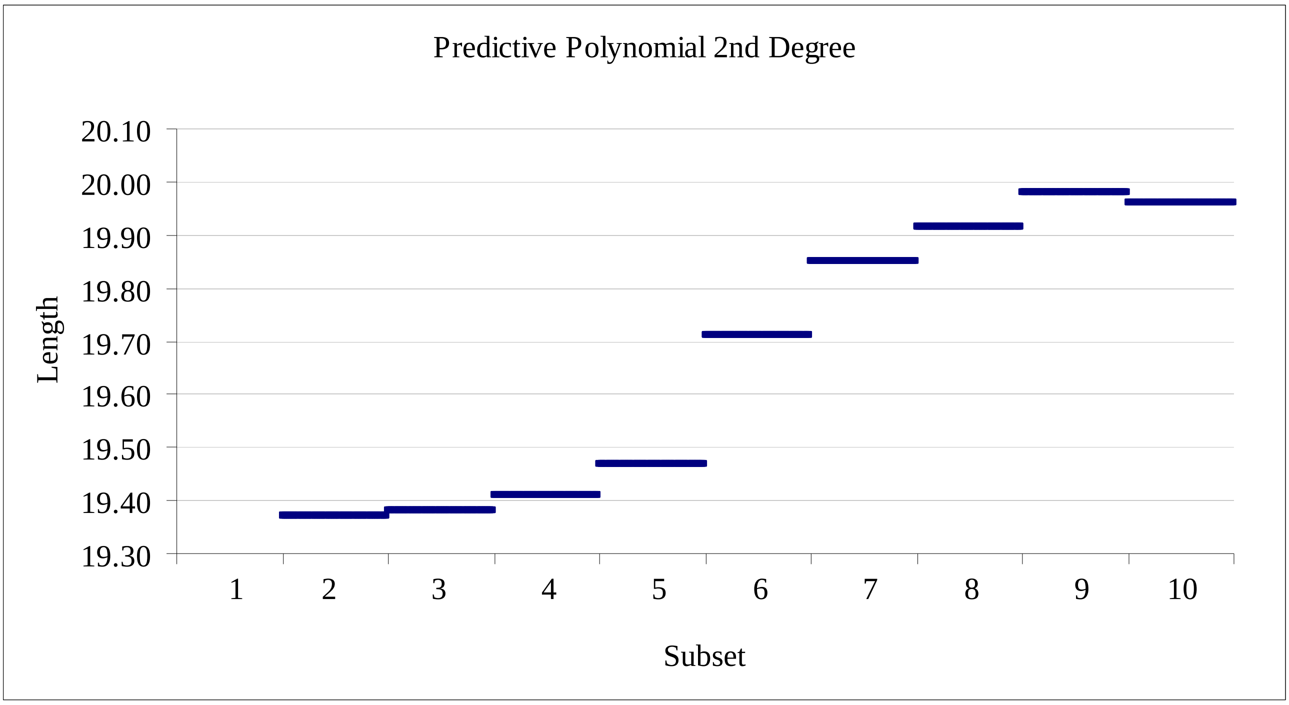

Figure A-8. Polynomial of 2nd degree – Predicted subset average values.

APPENDIX B. STATISTICS AND PROBABILITY

This section is mostly based on the work of Grinstead et al [Gri97 ch.7].

B.1 Sum of Two Independent Normal Random Variables

If *X* and *Y* are independent random variables and normally distributed, then their sum is also normally distributed

$$X \sim N\left(\mu_X, \sigma_X^2\right) \tag{B-1}$$

$$Y \sim N\left(\mu_Y, \sigma_Y^2\right) \tag{B-2}$$

$$Z = X + Y \tag{B-3}$$

$$Z \sim N\left(\mu_X + \mu_Y, \sigma_X^2 + \sigma_Y^2\right) \tag{B-4}$$

Since two separately (not jointly) normally distributed random variables can be uncorrelated without being independent, *X* and *Y* must be independent, not just uncorrelated. Otherwise, their sum can be non-normally distributed.

B.1.1 Proof by Convolutions

For random variables *X* and *Y*, the distribution f_Z of $Z = X + Y$ equals the convolution of f_X and f_Y:

$$f_Z(z) = \int_{-\infty}^{\infty} f_Y(z-x) f_X(x) dx \tag{B-5}$$

Given that f_X and f_Y are normal densities,

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma_X} e^{-\frac{(x-\mu_X)^2}{2\sigma_X^2}} \tag{B-6}$$

$$f_Y(y) = \frac{1}{\sqrt{2\pi}\sigma_Y} e^{-\frac{(y-\mu_Y)^2}{2\sigma_Y^2}} \tag{B-7}$$

Substituting equations (B-6) and (B-7) into the convolution in equation (B-5):

$$f_Z(z) = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma_Y} e^{-\frac{(z-x-\mu_Y)^2}{2\sigma_Y^2}} \frac{1}{\sqrt{2\pi}\sigma_X} e^{-\frac{(x-\mu_X)^2}{2\sigma_X^2}} dx \tag{B-8}$$

$$f_Z(z) = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sqrt{\sigma_X^2+\sigma_Y^2}} e^{-\frac{[z-(\mu_X+\mu_Y)]^2}{2(\sigma_X^2+\sigma_Y^2)}} \frac{1}{\sqrt{2\pi}\frac{\sigma_X\sigma_Y}{\sqrt{\sigma_X^2+\sigma_Y^2}}} e^{-\frac{\left(x-\frac{\sigma_X^2(z-\mu_Y)+\sigma_Y^2\mu_X}{\sigma_X^2+\sigma_Y^2}\right)^2}{2\left(\frac{\sigma_X\sigma_Y}{\sqrt{\sigma_X^2+\sigma_Y^2}}\right)^2}} dx \tag{B-9}$$

$$f_Z(z) = \frac{1}{\sqrt{2\pi}\sqrt{\sigma_X^2+\sigma_Y^2}} e^{-\frac{[z-(\mu_X+\mu_Y)]^2}{2(\sigma_X^2+\sigma_Y^2)}} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\frac{\sigma_X\sigma_Y}{\sqrt{\sigma_X^2+\sigma_Y^2}}} e^{-\frac{\left(x-\frac{\sigma_X^2(z-\mu_Y)+\sigma_Y^2\mu_X}{\sigma_X^2+\sigma_Y^2}\right)^2}{2\left(\frac{\sigma_X\sigma_Y}{\sqrt{\sigma_X^2+\sigma_Y^2}}\right)^2}} dx \tag{B-10}$$

The expression in the integral is a normal density distribution on x so the integral evaluates to 1. Thus, equation (B-4) is demonstrated.

$$f_Z(z) = \frac{1}{\sqrt{2\pi}\sqrt{\sigma_X^2+\sigma_Y^2}} e^{-\frac{[z-(\mu_X+\mu_Y)]^2}{2(\sigma_X^2+\sigma_Y^2)}} \tag{B-11}$$

B.1.2. Proof by Characteristic Functions

The characteristic function $\varphi_{X+Y}(t)$ of the sum of two independent random variables X and Y is the product of the two separate characteristic functions $\varphi_X(t)$ and $\varphi_Y(t)$ of X and Y.

$$\varphi_{X+Y}(t) = E(e^{it(X+Y)}) \tag{B-12}$$

$$\varphi_X(t) = E(e^{itX}) \tag{B-13}$$

$$\varphi_Y(t) = E(e^{itY}) \tag{B-14}$$

The characteristic function of the normal distribution with expected value μ and variance σ^2 is

$$\varphi(t) = e^{it\mu - \frac{\sigma^2 t^2}{2}} \tag{B-15}$$

so

$$\varphi_{X+Y}(t) = \varphi_X(t)\varphi_Y(t) = e^{it\mu_X - \frac{\sigma_X^2 t^2}{2}} e^{it\mu_Y - \frac{\sigma_Y^2 t^2}{2}} \tag{B-16}$$

$$\varphi_{X+Y}(t) = e^{it(\mu_X + \mu_Y) - \frac{(\sigma_X^2 + \sigma_Y^2)t^2}{2}} \tag{B-17}$$

Equation (B-17) is just the characteristic function of the normal distribution with expected value $(\mu_X + \mu_Y)$ and variance $(\sigma_X^2 + \sigma_Y^2)$. Thus, equation (B-12) is proved.

APPENDIX C: DYNAMIC ASSEMBLING SIMULATION SOFTWARE

C.1 Configuration Files

An example of DASS setting file is shown in Table C-1. The first columns have the setup of three different experiments. Each of them can be replicated as many times as desired, the results will be stored in separated tabs of an external MS Excel file.

Since DASS was conceived to be fully customizable, the user is completely free to introduce a wide range of different values and combination to simulate many scenarios.

Table C-1. Columns of the Configuration File

Setup 1	Setup 2	Setup 3	Parameter	Description
3	3	3	k-position	Position k of the component to be adjusted
1000	2000	3000	lot_size	Lot size
125	125	125	subset_size	Subset size
25	25	25	sample_rate	Inspection rate (samples per susbset)
1	2	3	sample_strat	Set the sampling strategy (1,2,3,4)
0	1	1	flag_cdna	Select either the sample mean or the cumulative de-noised avg.
100	100	100	uncertainty	Measurement uncertainty (%).
5000	5000	5000	clst_size	Cluster size
0	0	0	flag_movie	Enable / disable the display of 1D-problem movie.
0	0	0	flag_movie_3d	Enable / disable the display of 3D-problem movie.
0	0	0	flag_stats	Enable / disable the estimation the simulation time.
1	1	1	flag_mcmc	Select random of Monte Carlo based number generation.
0	0	0	flag_graph	Enable / disable all plotting functionalities..
1	1	1	flag_optm	Enable / disable the optimized algorithm for measurements
0	0	0	flag_cmpind	Select the compensation factor (%) to correct the mean shift
0	0	0	flag_allcomp	Select the positions to be simulated. Only K or all of them.
0	0	0	flag_delay	Set the response delay (%).
0	0	0	flag_pred	Enable / disable / set the predictor.
0	0	0	flag_feedback	Enable / disable feedback loop.

C.2 Superposition of the Variation

There are no few sources of variation whose footprints might leave a short and long-term trend (Figure C-1). For example, the tool wear. Other type of variation, however, describes an oscillating pattern as a result of, for instance, changes of temperature and tools dilatation (Figure C-2).

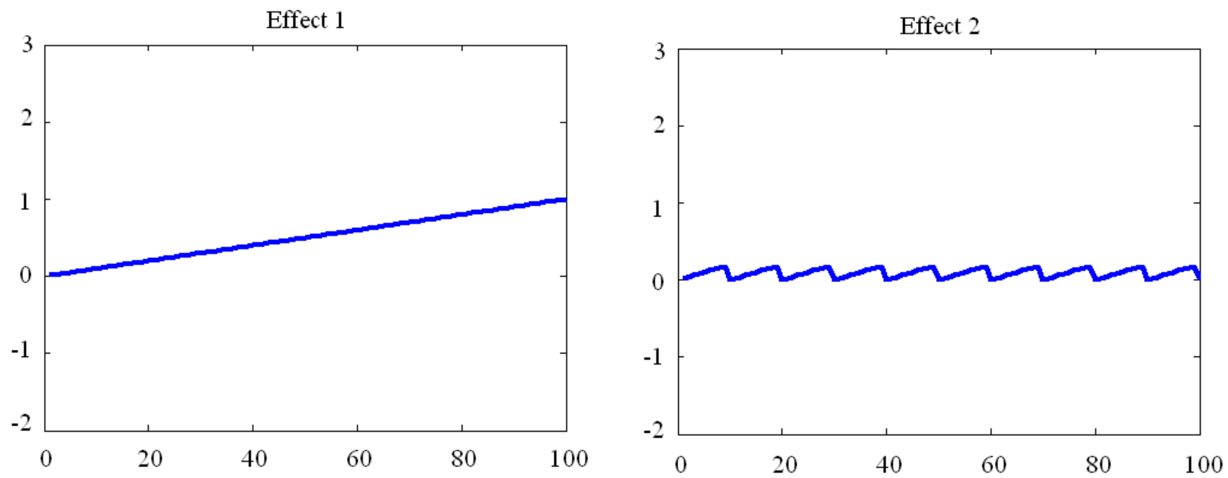

Figure C-1. Long and short term trends.

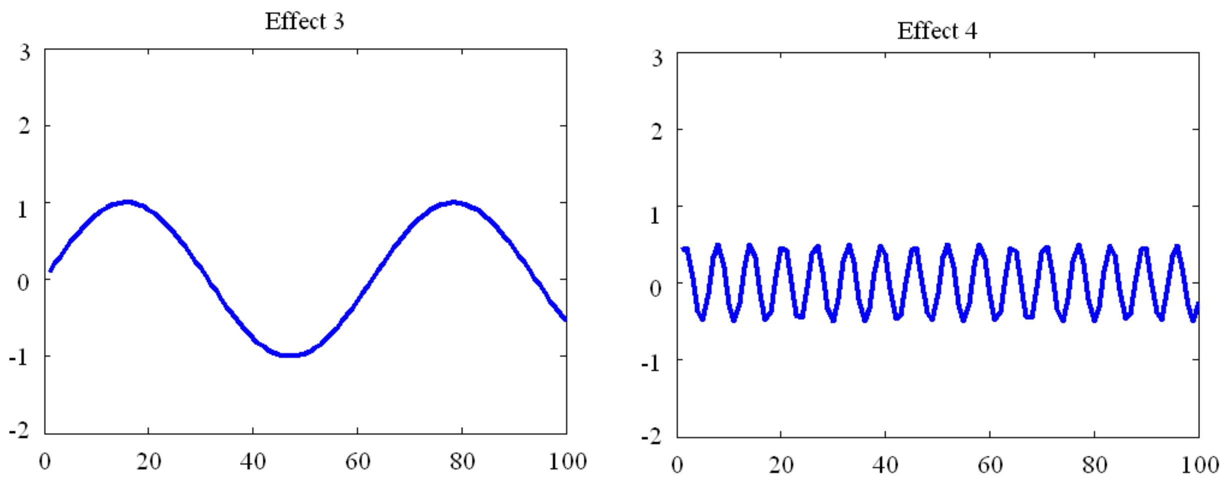

Figure C-2. Long and short term oscillations.

The superposition of the effects above can be seen in Figure C-3. This kind of variation is the one introduced by DASS in the component lots. The amplitude, frequency, slope and central point can be defined by the user in one of the setting file.

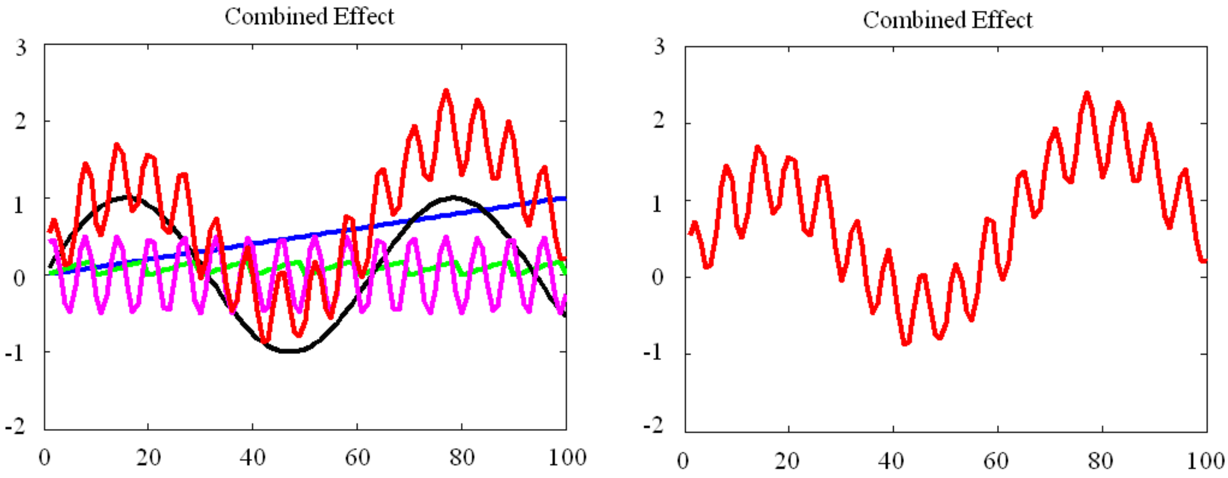

Figure C-3. Variation superposition.

C.3 Normality Test

DASS counts with some features to check the normality of the randomly (or Monte Carlo based) generated numbers that represent the length of the component items. Figure C-4 shows a lot of 1,000 items generated by DASS and that are expected to be normally distributed. The corresponding histogram is automatically generated (Figure C-5).

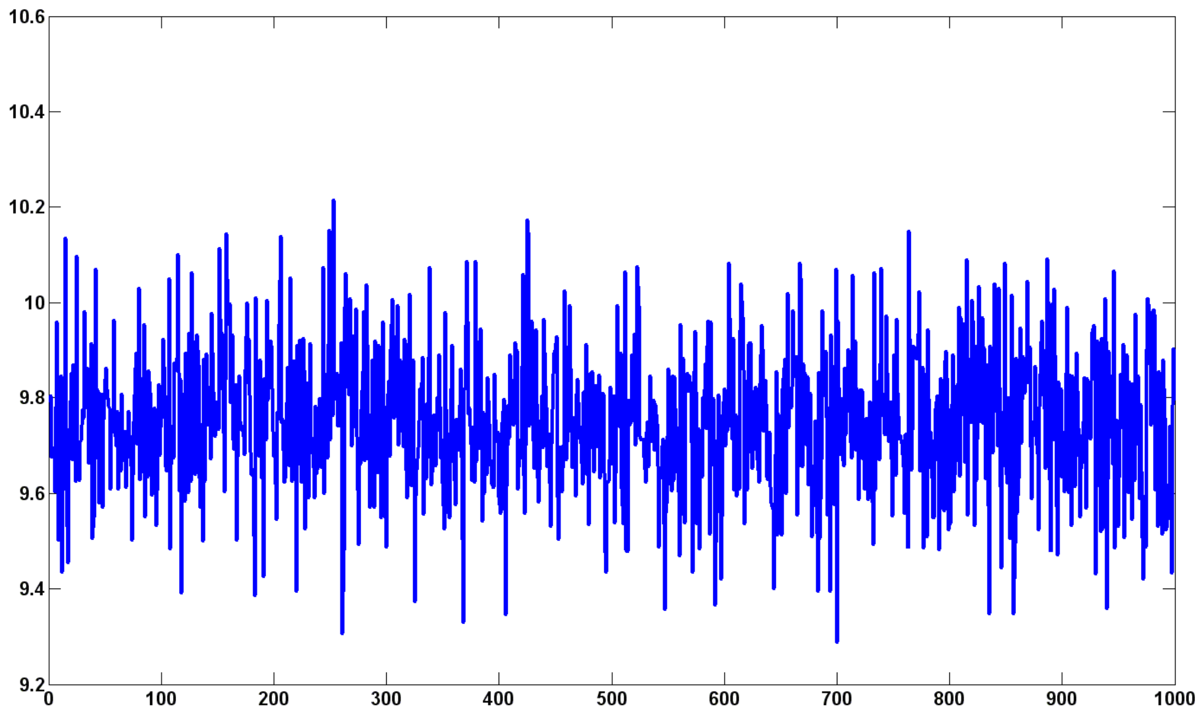

Figure C-4. Component lot.

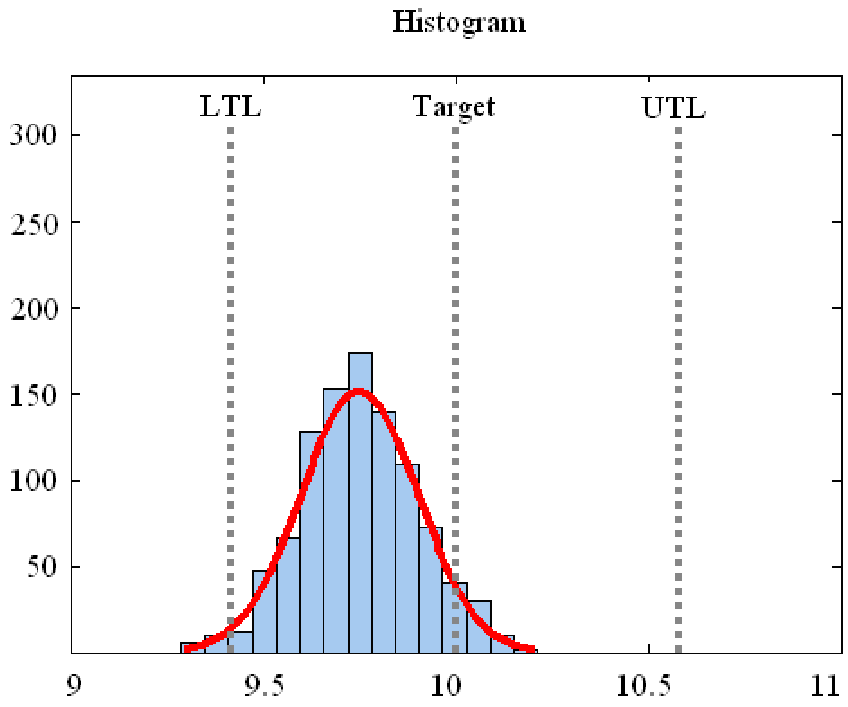

Figure C-5. Component lot's histogram.

Apparently the set of number describes a normal distribution. This can be checked with the help of a normality test plot that is also generated automatically by DASS (Figure C-6).

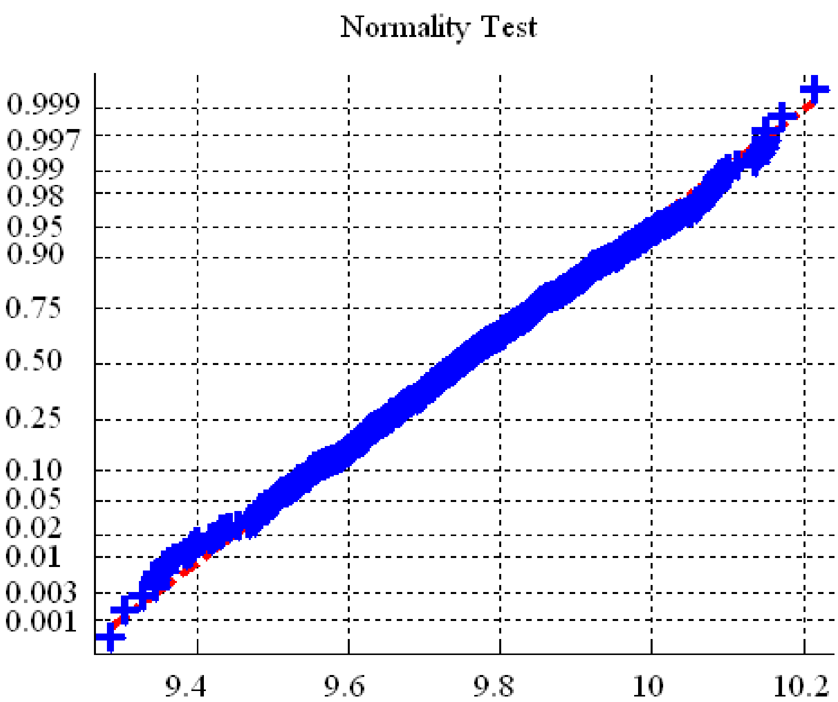

Figure C-6. Normality test.

C.4 Introduction of Variation

DASS converts the combined variation defined by the user in a variation vector that is used then to alter the vector containing the information of the component lots. The process was already explained in Chapter 3 and Chapter 4.

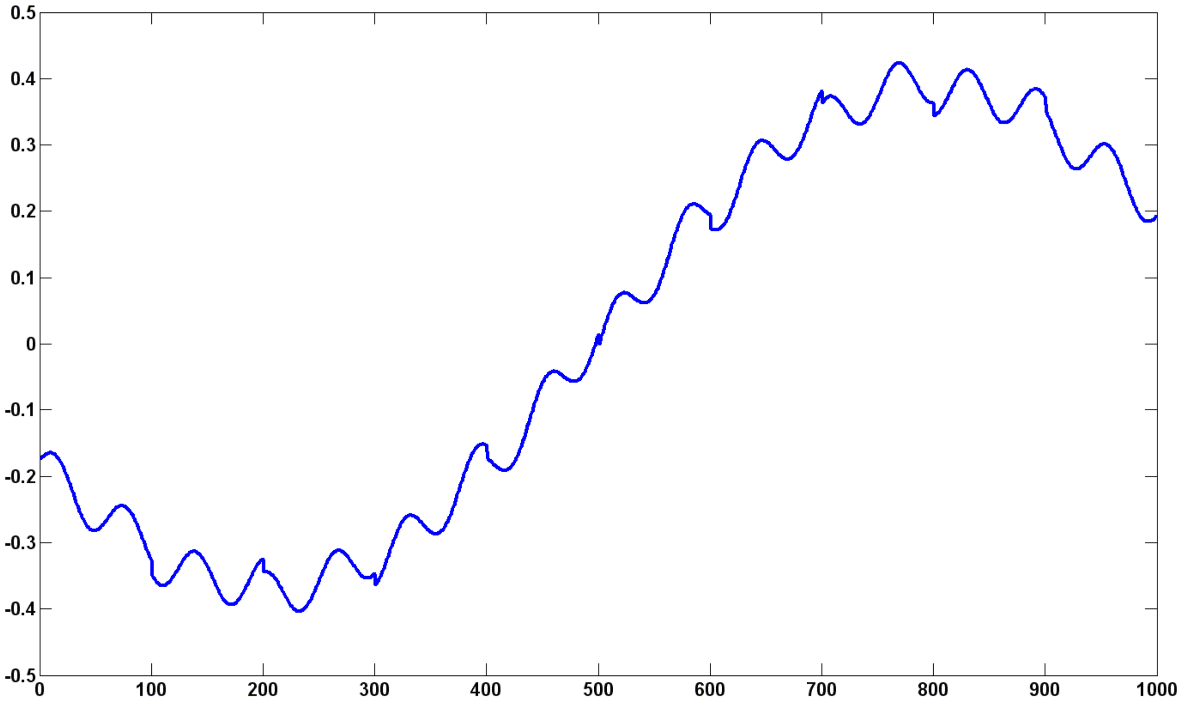

Figure C-7. Combined variation vector.

Once the variation vector (Figure C-7) has been introduced in the component vector like the one in Figure C-4, but not necessarily that one, the altered component vector will evidence the presence of the variation (Figure C-8).

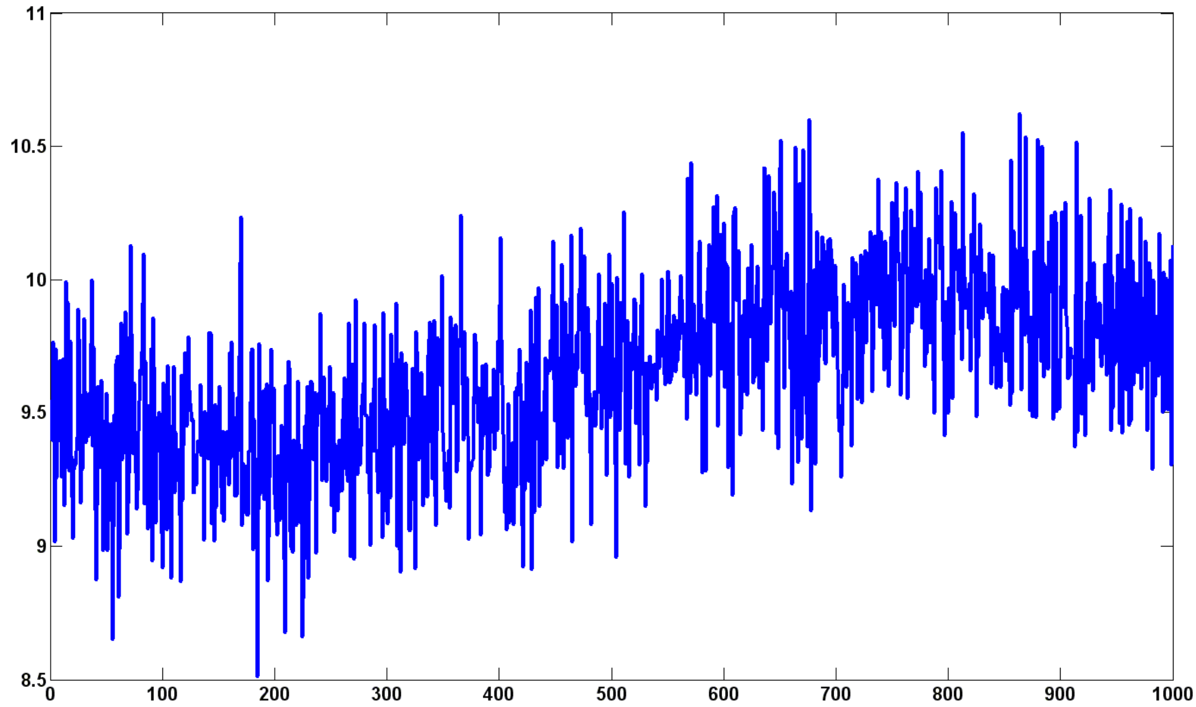

Figure C-8. Component lot after the introduction of the variation.

The corresponding histogram is shown in Figure C-9. As expected, it is a normal distribution.

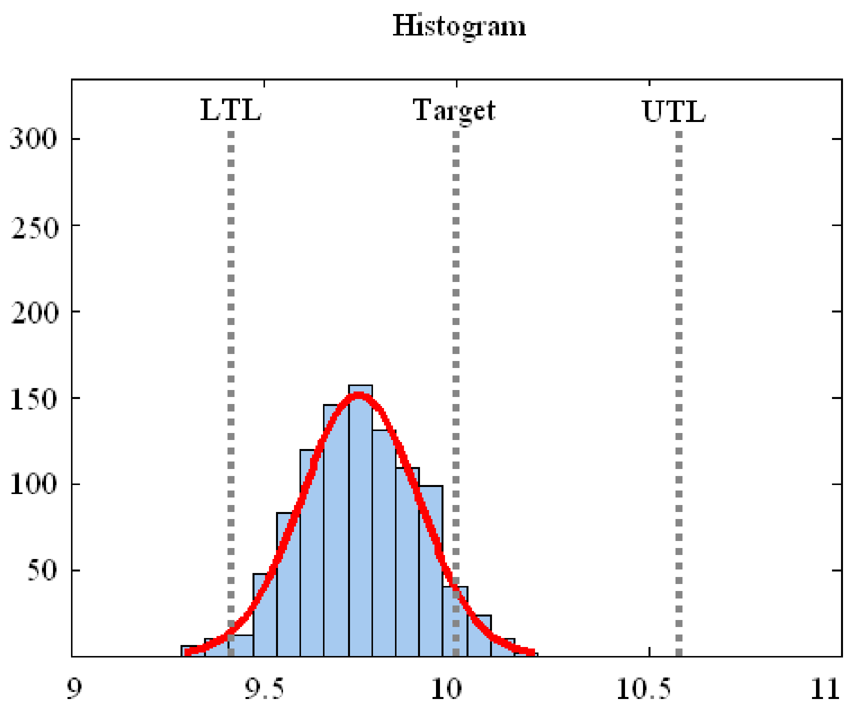

Figure C-9. Histogram of the altered component lot.

The normality can be confirmed with the help of the normality test (Figure C-10). This example shows that the procedure followed to introduce the variation vector and to rectify the mean and standard deviation of the altered vector is correct.

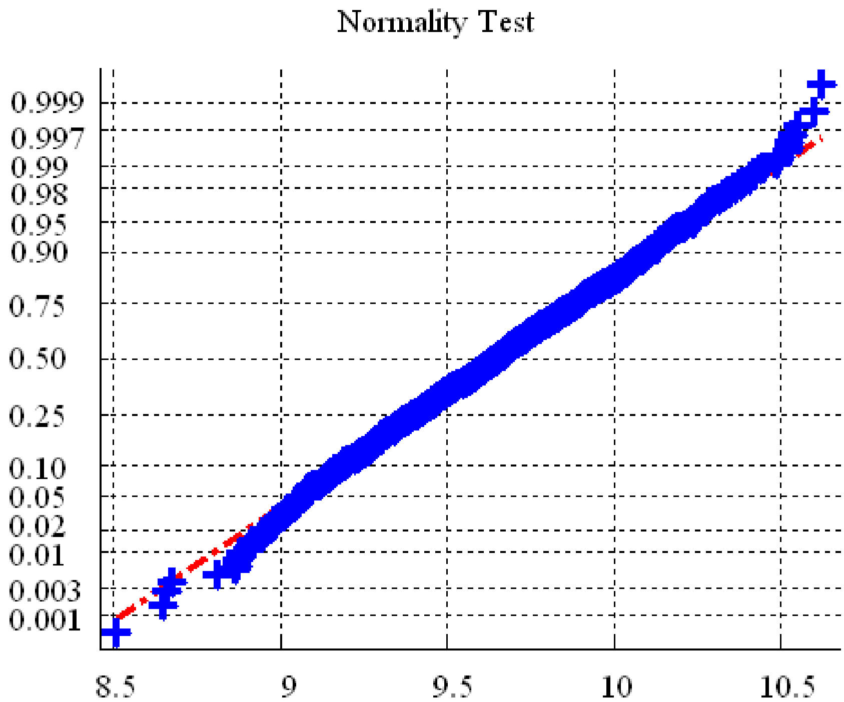

Figure C-10. Normality test of the altered component lot.

C.5 Plotting: 2D and 3D

DASS is featured to produce automatically a wide range of plots and comparison charts. Some of most attractive are the 3D plots.

In Figure C-11 the difference between a randomized assembling and the application of SFFCM is shown. In this case, it is an assembly made of three components, being the one in the middle (*k=2*) the adjusted component.

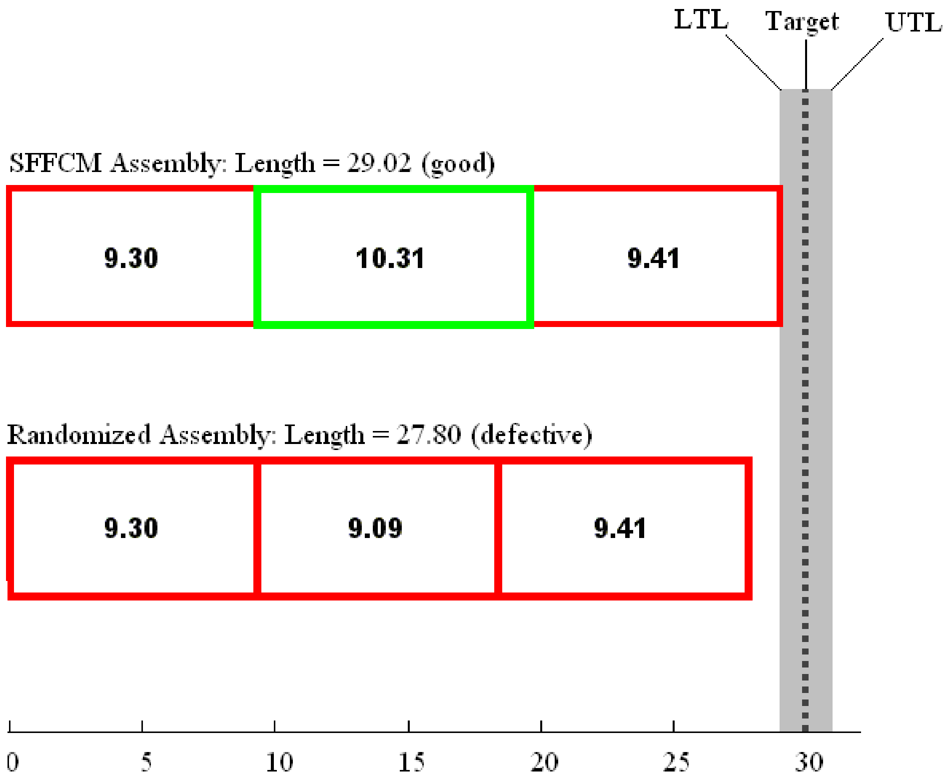

Figure C-11. Plot of the one-dimensional problem.

An equivalent situation if depicted in Figure C-12, albeit in 3D. Again, the component whose target and tolerance have been adjusted is in the middle.

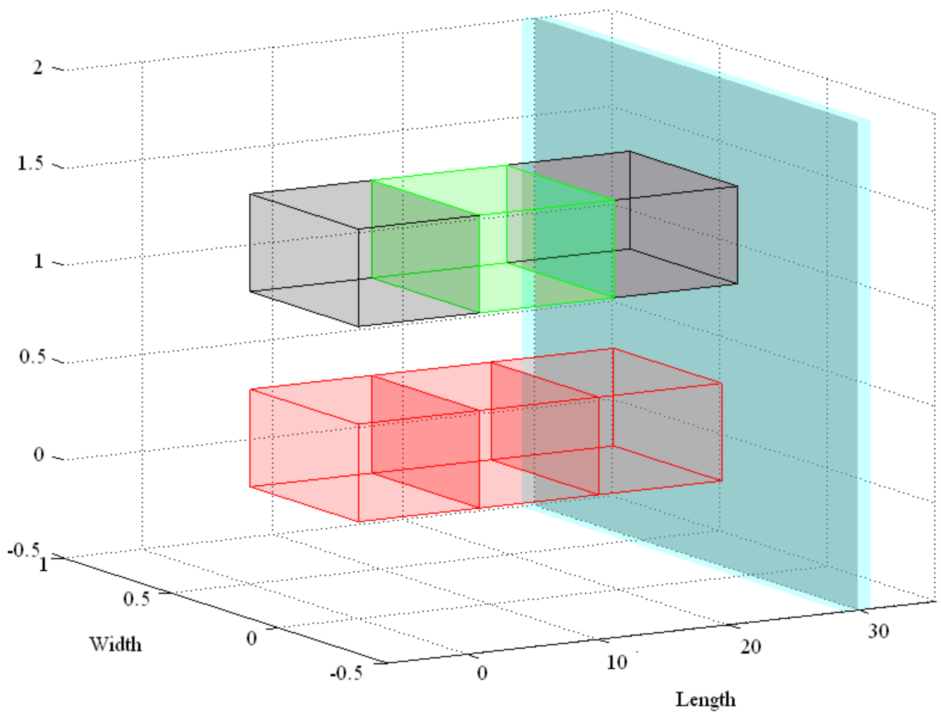

Figure C-12. 3D-Plot of the one-dimensional problem.

A still novel application of SFFCM for 3D problems is shown in Figure C-12. In this case, the tolerance zone of the assembly is the volume where the tolerance planes intersect each other.

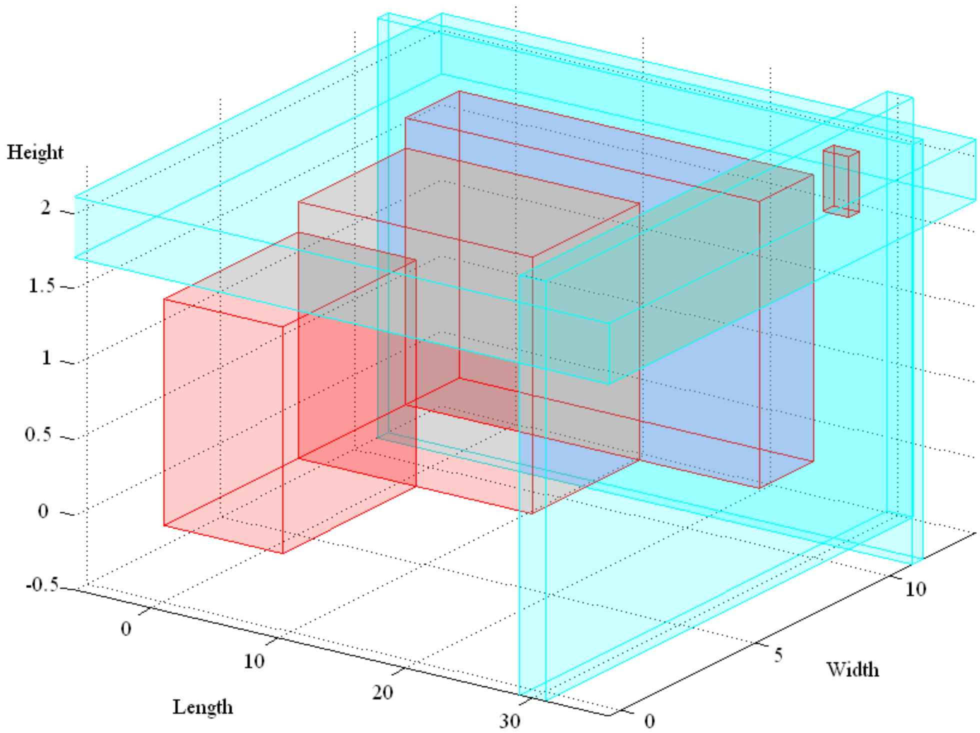

Figure C-13. 3D-Plot of the three-dimensional problem.